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El Niño, Expectations, and Fishing Effort in Monterey Bay, California

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This article uses vector autoregressions (VARs) and a dynamic linear rational expectations model to analyze the effects of sea surface temperatures and catch prices on fishing effort for albacore tuna, Chinook salmon, sablefish, and squid in Monterey Bay, California. The VAR results show that fluctuations in sea surface temperatures, including El Niño events, have significant effects on effort and prices for these fisheries. Estimation of the model shows that El Niño has positive effects on the abundance in Monterey Bay of albacore and negative effects on Chinook, sablefish, and squid. Testing of the model supports rational expectations by harvesters of albacore, Chinook, and sablefish but not squid. Test results also suggest that dynamic adjustment costs are not significant for albacore, Chinook, or sablefish fisheries.

1. INTRODUCTION

In 1976, the Magnuson Fishery Conservation and Management Act established a new era for U.S. marine resource management, giving federal jurisdiction over fisheries 3–200 miles from the coast. Under the Magnuson Act, catch by foreign fleets in the 3–200-mile zone dropped to zero by 1992. This drop was more than matched by a rapid expansion of the U.S. domestic fleet: since 1977, the total fish harvest from this zone increased by more than 300% to a peak of 6.6 billion pounds annually by 1986, but then declined [2]. Recognizing that the survival of many fisheries was threatened, Congress passed the Sustainable Fisheries Act (SFA) in 1996 to amend the Magnuson Act. The SFA amendments include management and conservation by the National Marine Fisheries Service (NMFS). In a recent report, the NMFS [7] identifies the incorporation of economic objectives as an essential next step in fisheries management. The report predicts that fisheries management will become more intensive, extensive, and contentious in the near future. As this occurs, according to the report, information that allows NMFS to quantitatively demonstrate that its policies have the highest net benefit to society will be critical.

To quantitatively analyze fisheries regulations and policy, empirical work is necessary to determine what outcomes would have been under alternative scenarios.

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Economists are familiar with this problem, which Robert Lucas and Thomas Sargent [5] summarize: "We observe an agent, or collection of agents, behaving through time; we wish to use these observations to infer how this behavior would have differed had the agent's environment been altered in some specified way." To make these inferences, Lucas and Sargent conclude that "the problem of identifying a structural model from a collection of economic time series must be solved." Identifying structural fisheries models appears to be an essential prerequisite for the type of policy evaluation required by NMFS.

Robert Rosenman [10] applies the theory of dynamic linear rational expectations models, with quadratic adjustment costs for changes in fishing effort, to analyze optimal fisheries management. This work focuses on the differences between private and social decisions about fishing effort and abstracts from the effects of climate and catch prices. Rosenman [11] uses a similar fisheries model that includes both catch prices and climate. In this work, Rosenman formulates his model as a multivariate vector autoregression (VAR) and applies it to time series data for Atlantic mackerel. Rosenman's VAR includes the cross-equation restrictions implied by rational expectations and strict exogeneity assumptions for catch prices and climate. The cross-equation restrictions are used to identify parameters and are not tested. Rosenman's results show that sea bottom temperatures do not significantly affect the Atlantic mackerel fishery. However, mackerel biology suggests that using surface instead of bottom temperatures could increase the significance of climate in Rosenman's analysis. In addition, Rosenman's price–climate exogeneity assumptions may exclude other important links between fisheries and climate.

Climate fluctuations are a driving force in Pacific fisheries [6]. For California fisheries, El Niño–Southern Oscillation (ENSO) events are among the most important sources of climate variability. These events occur about every 3–7 years, may be associated with extreme changes in climate, and are a major source of global interannual climate variability [16]. An ENSO event is characterized by a relaxation of trade winds in the equatorial Pacific that causes the movement of abnormally warm water into the eastern Pacific. According to NMFS, ENSO events cause important fluctuations in the abundance of mackerel, squid, salmon, tuna, and other species. Fluctuations in abundance, from climate and other factors, interact with the dynamics of catch prices to affect the allocation of fishing effort. For example, NMFS [7] describes a fleet of about 600 small trollers operating off the coast of California, Oregon, and Washington. Unlike purse seiners, these vessels are easily adapted to alternate between fisheries. Consequently, most Pacific coast trollers fish for tuna, salmon, and crab, depending on the relative availability and price of each.

This article examines links between fisheries economics and climate in Monterey Bay, California, by analyzing the significance and structure of relationships between fishing effort, catch prices, and sea surface temperatures. Part of the analysis in this article focuses on the validity of the rational expectations hypothesis and the importance of dynamic adjustment costs in describing decisions about fishing effort. Empirical work on these topics is limited and provides little evidence about the behavior of harvesters in response to uncertainty, or which factors are important in decisions about fishing effort. However, a good understanding of these factors seems essential for successful fisheries management.

Section 2 of this article describes recent fisheries and climate time series data from Monterey Bay, California. Section 3 presents VAR results from these data. Section 4 develops a dynamic linear rational expectations fisheries model and analyzes cases with nonzero and zero adjustment costs. Section 5 presents results from estimation and testing of the model. Section 6 discusses results and their policy implications and suggests several directions for future research.

2. FISHERIES AND CLIMATE DATA

This article analyzes four commercial fisheries of Monterey Bay, California: albacore tuna, Chinook salmon, sablefish, and squid. The fisheries of Monterey Bay are an important part of the economic, cultural, and literary heritage of the region, California and the United States, including John Steinbeck's novel *Cannery Row*. On average from 1981 to 1995, Monterey Bay ports (Monterey, Moss Landing, and Santa Cruz) landed 26.4 million pounds of fish and earned $6.3 million per year from catch revenues, accounting for 5–10% of the total California catch [15]. From Table I, albacore, Chinook, sablefish, and squid accounted for more than 50% of total commercial fishery revenues for Monterey Bay ports from 1981 to 1999. These four fisheries also represent a range of biological and gear types. The albacore is an open water or pelagic species that is highly mobile and migratory. The Chinook is anadromous, spending parts of its life in marine and freshwater habitats. The sablefish is a roundfish that is most abundant in deeper water near the ocean bottom. The squid is an invertebrate that schools in deeper water but moves inshore to spawn. Albacore and Chinook are primarily caught by trolling. Sablefish are caught using a variety of gear types and methods, including long lines, traps, and bottom trawling. Squid are caught with purse seines, and you can often see the bright lights of the squid boats off the coast of Monterey before moonrise.

This article uses time series data from the Pacific States Marine Fisheries Commission (PSMFC) Pacific Fisheries Information Network (PacFIN). The PacFIN data in this article cover the period 1981–99 and include catch, catch prices, and fishing effort. The data were collected from individual trip tickets for fishing vessels landing their catch at Monterey Bay ports. The data on each trip ticket include vessel identification, landed weights of each species, information on catch location, and date and port of landing. Table I presents percentage shares

TABLE I
Monterey Bay Fisheries Percentage Shares

	Revenues		Landings		Vessels	
	1981–99	1995–99	1981–99	1995–99	1981–99	1995–99
Albacore	7.642	6.114	2.740	1.961	4.743	4.742
Anchovy	2.514	3.492	9.468	9.795	0.387	0.458
Bocaccio and chillipepper	5.262	4.065	4.074	2.301	3.713	4.202
Chinook	21.163	19.281	2.942	3.717	18.608	15.251
Dover sole	3.196	3.282	3.282	2.656	0.809	1.664
Rockfish	5.191	0.735	4.031	0.314	8.581	4.227
Sablefish	4.958	10.047	2.555	2.076	2.106	3.919
Sardine	3.105	7.620	17.783	47.251	0.406	0.849
Squid	15.785	8.290	31.574	13.996	1.159	0.807
Swordfish	8.587	8.340	0.997	0.953	1.093	1.165

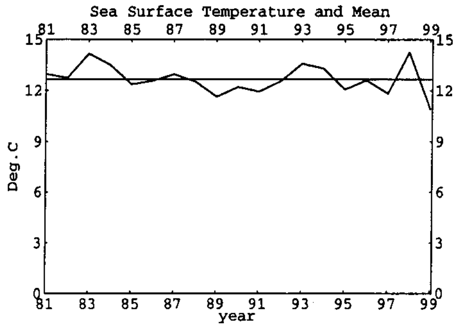

FIG. 1. Sea surface temperatures.

for real commercial revenues, weight of total commercial landings, and number of commercial fishing vessels from 1981 to 1999 and 1995 to 1999 from PacFIN data for Monterey Bay.[2] The statistics in Table I identify fisheries with the greatest economic value in Monterey Bay. Albacore, Chinook, squid, and swordfish have the greatest economic value from 1981 to 1999, but the value of the growing sablefish fishery is greater than albacore or swordfish from 1995 to 1999.

Following [6], this article describes climate with November–March average daily sea surface temperatures (SST). Daily observations are taken from Hopkins Marine Station in Pacific Grove, California. Sea surface temperature anomalies (SSTA) are differences of SST for each year from the 1981–99 mean. Figure 1 plots SST and the 1981–99 mean and shows three major ENSO events with SSTA peaks of 1.2 °C in 1983, 1.0 °C in 1993, and 1.9 °C in 1998.

This article measures fishing effort by the number of vessels or boats landing an individual species.[3] Two aggregate measures of fishing effort are available from PacFIN: total fishing trips and total number of fishing boats. A common aggregate measure of fishing effort is the total number of boat days fished. Information on boat days is not available from the PacFIN trip ticket data.[4] However, this article

[2]This article measures real values in 1990 U.S. dollars calculated from the Producer Price Index for crude foodstuff and feedstuff commodities from the Bureau of Labor Statistics. The fisheries in Table I earned at least 2.0% of the total for all Monterey Bay commercial fisheries. Table I calculates revenue shares by dividing fishery revenues for 1981–99 and 1995–99 by the total for all Monterey Bay fisheries reported in the PacFIN data. Fishery landings in PacFIN are measured in metric tons.

[3]An important issue for the analysis in this article is whether to analyze catch or fishing effort. Much of the fisheries literature examines catch as the choice variable for decision makers. However, Rosenman [10] observes that from the point of view of fishing vessel operators, fishing effort is the appropriate choice variable since catch from their point of view is uncertain and is affected by effort. Catch may be the appropriate choice variable from a fishery manager's perspective, but this article analyzes decisions made by individual fishing vessel operators and therefore models fishing effort as a choice variable.

[4]Rosenman [11] uses the total number of boat days as an aggregate measure of fishing effort in his study of the Atlantic mackerel fishery, and he formulates dynamic adjustment costs in these terms. Aggregate measures of fishing effort, including number of boats, boat trips, and boat days, are imperfect. A consistent measure of fishing effort, such as the one constructed by Squires [14], would be better suited for the analysis in this article, but data with the necessary level of detail do not exist. The PSMFC recently began collecting the cost and input data required for more detailed measures of fishing effort in its Fisheries Economics Data Program.

analyzes the significance of dynamic adjustment costs in the allocation of fishing effort. Among aggregate measures of effort, dynamic adjustments in the number of vessels targeting an individual species are likely to be costly relative to changes in the number of days fished or fishing trips.[5]

A description of the regulatory setting and relevant policies are important features missing from the data used in this article that should be addressed in future work. The range of regulation for albacore, Chinook, sablefish, and squid varies widely. There is practically no regulation of squid. While there was little direct regulation of sablefish until after the Magnuson Act, this fishery is now controlled by restrictions on boat trips and gear type. There are moderate regulations for albacore, including dolphin-safe gear restrictions. Chinook are extensively managed by season, gear type, and other policies [15].

3. VESSELS, PRICES, AND SST

Data used in this article for analyses of Chinook, sablefish, and squid fisheries are differences from means that are defined by regressing time series for fishing boats, catch prices, and SST on constants. To avoid numerical problems, data used for analysis of the albacore fishery are detrended by regressing the time series on constants and linear trends. Residuals from these regressions are covariance stationary, and their use as data simplifies statistical work below by allowing constants to be omitted from the estimating equations.[6]

Figure 2 shows numbers of boats, catch prices, trends for albacore, and means for Chinook. Figure 3 shows numbers of boats, catch prices, and their means for sablefish and squid. Correlation between boats, prices, and SST, particularly for albacore and squid, is apparent from Figs. 1–3.[7] Data that are differences from means and trends in these figures are normalized by 1983 values prior to further empirical work. Since 1983 was the peak of a major ENSO, this normalization provides a useful reference or benchmark for results presented below.

In this article, a trivariate VAR for each fishery analyzes empirical relationships between boats, prices, and SST. The VAR for each fishery includes SST and data for boats and prices for that fishery only, thus ignoring any significant interactions

[5]For example, the costs of changing the number of boat days or boat trips for a fixed fleet would be relatively minor compared to moving vessels into or out of a fleet fishing for a particular species. Important examples of the adjustment costs related to entering or exiting a fleet could include travel to or from home port, gear switching or installation, purchasing or selling permits, and other relatively fixed costs related to equipment or regulation.

[6]Mathematica 4.0 and a Silicon Graphics O_2 workstation produced the empirical results in this article. Copies of the Mathematica programs and data are available from the author. Numerical calculation of impulse response functions, described below, required detrended data for albacore. Other results for albacore are robust to using data that are differences from means. However, for consistency, detrended data are used for albacore throughout the article.

[7]No squid were landed at Monterey Bay ports in 1998, corresponding to the major ENSO during that year. Consequently, a market price for squid in 1998 does not appear in the PacFIN data. For the empirical work in this article, the average catch price for squid from 1981 to 1999, excluding 1998, is used for the missing 1998 catch price.

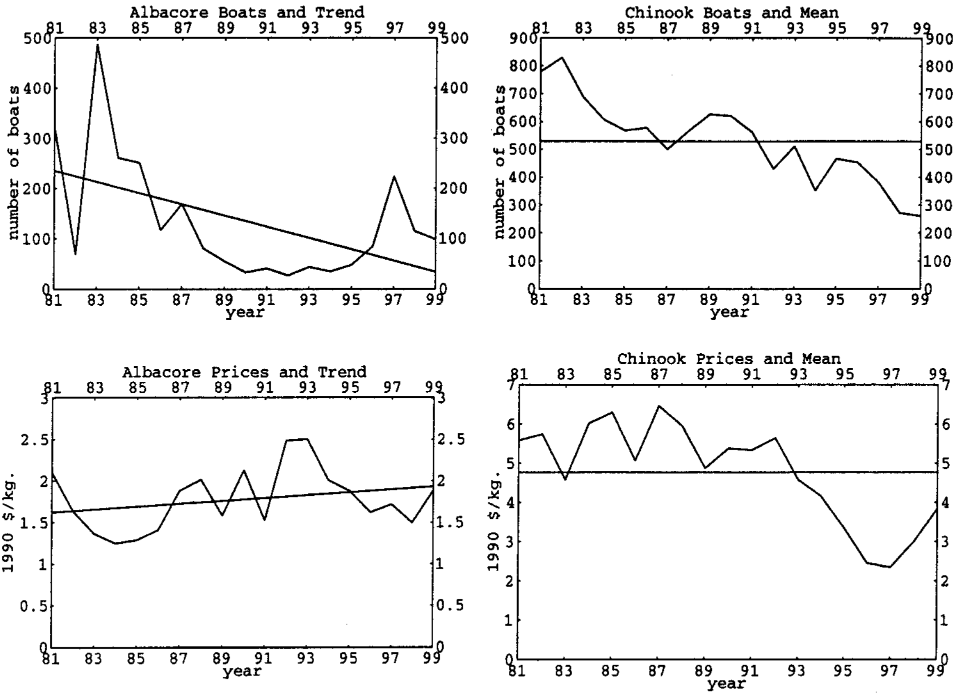

FIG. 2. Albacore and Chinook.

between fisheries.[8] The first set of VARs includes fourth-order lags, the allowable maximum.[9] A likelihood ratio statistic described in [3] tests lower order restrictions of the fourth-order VARs. The test statistic has a χ^2 distribution and is modified to reduce small sample bias. Generally, this article uses the lowest order VAR that is statistically acceptable which does not create numerical problems during further analysis, specifically during computation of the impulse response functions described below. Consequently, this article uses first-order VARs for albacore, Chinook, and squid and a second-order VAR for sablefish.[10] Table II presents the χ^2 test statistics and significance levels, which are values of the distribution greater than the test statistic, for each fishery.

[8]Interactions between fisheries may be significant. Two main fleets operating in Monterey Bay are trollers and purse seiners. Trollers may switch between albacore and Chinook. The seiners focus on squid but may also target anchovy, mackerel, or sardine. An analysis of these interactions is planned for future work. For the empirical work in this article, switching costs are summarized by the adjustment cost model described below, with the interpretation that changes in fishing effort for a single fishery are relative to a single alternative activity. Future work could decompose the single adjustment cost parameter for each fishery in this article into components that correspond to different fisheries.

[9]There are $3 \times 4 = 12$ regression coefficients in each equation, conditional on 4 years of data, which reduces the sample size from 19 to 15 years.

[10]Numerical calculation of impulse response functions, described below, required a second-order VAR for sablefish. Like results for albacore with detrended data, other results for sablefish are robust to using a second-order VAR for analysis. Each first- and second-order VAR equation has three or six estimated coefficients, respectively, since constants are omitted from the estimating equations. Therefore, the number of restrictions implied by each first-order VAR is $9 \times 3 = 27$, and that for the second-order VAR is $6 \times 3 = 18$. These values are the degrees of freedom for each test.

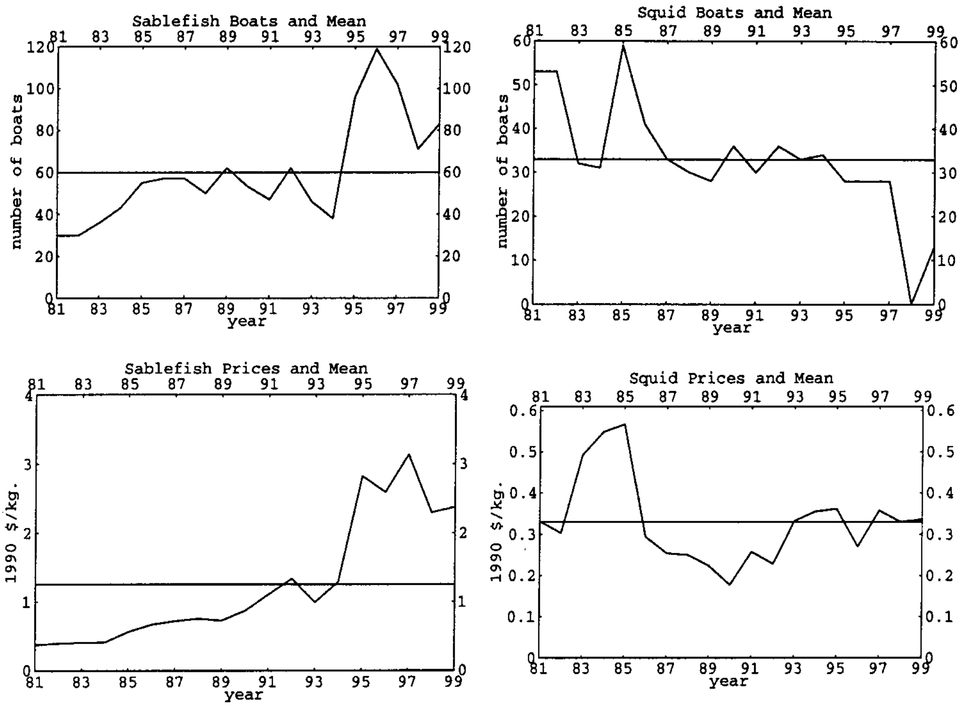

FIG. 3. Sablefish and squid.

Table III presents VAR results for albacore and Chinook, including least-squares parameter estimates, standard deviations, t-statistics, two-tailed significance levels, and the R^2 of each regression. Table IV presents this information for sablefish and squid. In each estimating equation, γ_j, $j = 1, 2, 3$, are the coefficients on the 1-year lags of data for boats, prices, and SST, respectively; the coefficients for sablefish of γ_j, $j = 4, 5, 6$, correspond to the 2-year lags for these variables.

The first- and second-order VARs presented in Tables III and IV summarize the dynamics of boats, prices, and SST for albacore, Chinook, sablefish, and squid. To illustrate the dynamics summarized by Tables III and IV, consider the effects on boats and prices for each fishery of a one-time impulse in SST from its mean value. Since the data are covariance stationary, the autoregressive models presented in Tables III and IV may be inverted to obtain moving average representations that are illustrated by the orthogonalized impulse response functions in Fig. 4.

The results in Fig. 4 show responses of boats and prices for 50 years following a unit increase in normalized SSTA as percentage differences from trends for alba-

TABLE II
First- and Second-Order VAR Tests

Fishery	Stat.	Sig.
Albacore	9.405	0.999
Chinook	7.072	1.000
Sablefish	7.481	0.985
Squid	10.405	0.998

TABLE III
First-Order VARs for Albacore and Chinook

	Albacore				Chinook			
Parameter	Est.	SD	T-stat.	Sig.	Est.	SD	T-stat.	Sig.
Boat equations								
γ_1	−0.206	0.263	−0.784	0.445	0.619	0.159	3.888	0.001
γ_2	0.154	0.076	2.038	0.060	−0.049	0.021	−2.268	0.039
γ_3	0.183	0.148	1.233	0.237	−0.047	0.228	−0.205	0.840
R^2	0.260				0.756			
Price equations								
γ_1	1.233	0.802	1.537	0.145	−1.564	1.402	−1.115	0.282
γ_2	0.172	0.231	0.744	0.468	0.659	0.188	3.500	0.003
γ_3	0.027	0.453	0.061	0.953	−2.043	2.005	−1.019	0.324
R^2	0.260				0.650			
SST equations								
γ_1	0.694	0.496	1.398	0.182	0.293	0.189	1.551	0.142
γ_2	−0.189	0.143	−1.325	0.205	0.017	0.025	0.687	0.502
γ_3	−0.371	0.280	−1.323	0.206	−0.145	0.271	−0.535	0.601
R^2	0.182				0.163			

core and means for Chinook, sablefish, and squid. According to the normalization described above, the unit increase in normalized SSTA corresponds to the 1983 ENSO of 1.2 °C. Since the data are covariance stationary, Fig. 4 shows responses for each fishery returning to means and trends following the SSTA. The impulse response functions predict an increase of about 15% in boats landing albacore after

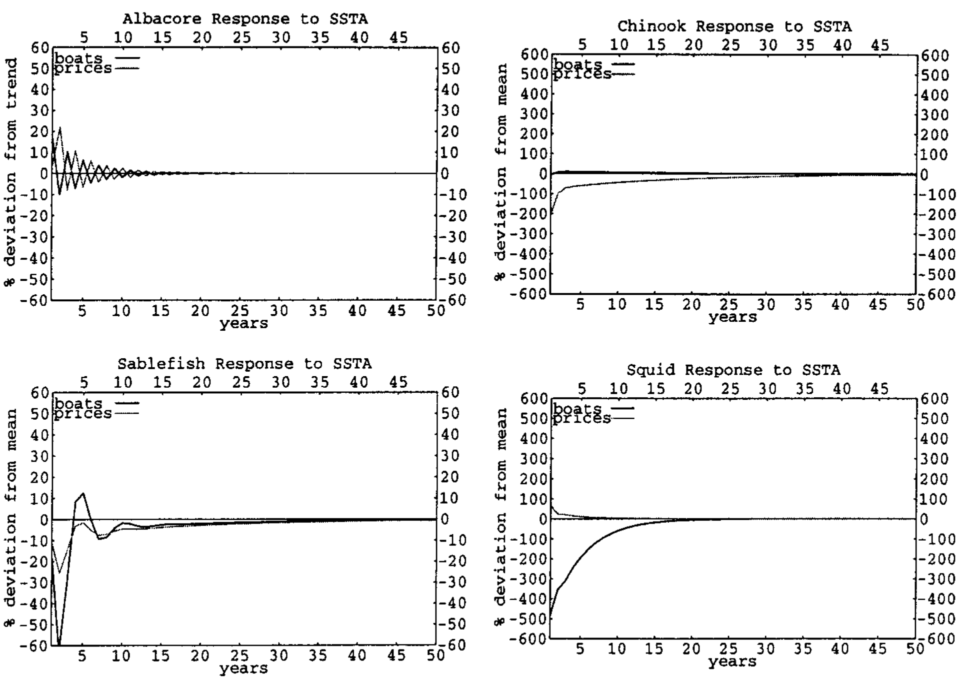

FIG. 4. Impulse responses to SSTA.

TABLE IV
Second-Order VAR for Sablefish and First-Order VAR for Squid

	Sablefish				Squid			
Parameter	Est.	SD	T-stat.	Sig.	Est.	SD	T-stat.	Sig.
Boat equations								
γ_1	0.284	0.358	0.793	0.444	0.524	0.237	2.215	0.043
γ_2	0.725	0.448	1.620	0.134	−2.212	5.040	−0.439	0.667
γ_3	−0.170	0.458	−0.371	0.718	−4.837	6.706	−0.721	0.482
γ_4	−0.418	0.382	−1.095	0.297				
γ_5	0.126	0.608	0.207	0.839				
γ_6	−0.504	0.439	−1.149	0.275				
R^2	0.717				0.313			
Price equations								
γ_1	−0.104	0.351	−0.298	0.771	−0.006	0.009	−0.626	0.541
γ_2	0.855	0.438	1.950	0.077	0.384	0.199	1.926	0.073
γ_3	−0.106	0.448	−0.236	0.818	0.669	0.265	2.526	0.023
γ_4	−0.207	0.374	−0.554	0.591				
γ_5	0.337	0.595	0.566	0.583				
γ_6	−0.183	0.430	−0.425	0.679				
R^2	0.767				0.566			
SST equations								
γ_1	0.198	0.368	0.539	0.601	−0.019	0.011	−1.783	0.095
γ_2	−0.479	0.460	−1.041	0.320	0.081	0.228	0.354	0.728
γ_3	−0.006	0.470	−0.014	0.989	−0.095	0.304	−0.314	0.758
γ_4	−0.166	0.392	−0.424	0.680				
γ_5	0.571	0.625	0.914	0.381				
γ_6	−0.086	0.451	−0.191	0.852				
R^2	0.162				0.242			

the SSTA followed by damped oscillations of both boats and prices around their trends. For Chinook, the predicted response for boats is relatively small, but prices respond by dropping nearly 200%. For sablefish, the predicted responses for boats and prices are declines of about 60% and 25%, respectively. For squid, the predicted response for boats is a decrease of more than 400%, and prices respond by increasing by about 50%.

The VARs in Tables III and IV provide alternative hypotheses for tests of Granger causality for each fishery among boats, prices, and SST. A multivariate test from [3], based on a likelihood ratio statistic with a χ^2 distribution, characterizes Granger causality among these variables. Table V presents statistics and significance levels for these tests. The values of X-b, X-p and X-s denote the χ^2 statistics corresponding to VARs that under the null hypothesis exclude boats, prices, and SST from the regressions, respectively. At a significance level of 5%, the statistics for each fishery in Table V do not reject restrictions that exclude effects of boats on prices and SST. On the other hand, at that level, statistics in Table V do reject restrictions that exclude effects of prices on boats and SST. Statistics in Table V also reject restrictions that exclude effects of SST on boats and prices at the 5% level.

Results for each fishery in Table V imply that prices Granger cause boats but that boats do not Granger cause prices. This fact supports a modeling assumption below that prices are exogenous to individuals' decisions about fishing effort. In

TABLE V
Granger Causality Tests

	Albacore		Chinook		Sablefish		Squid	
Test	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
X-b	4.581	0.101	4.143	0.126	1.622	0.805	3.631	0.163
X-p	14.138	0.001	7.734	0.021	22.596	0.000	5.850	0.054
X-s	11.244	0.004	7.333	0.026	15.870	0.003	7.922	0.019
Xs-b	0.952	0.329	2.328	0.127	0.551	0.759	4.971	0.026

addition, results in Table V imply that SSTs Granger cause boats and prices, which shows that climate fluctuations have significant effects on each fishery. Evidence of a direct link between climate and decisions about fishing effort is provided by SST Granger causing boats; evidence of an indirect link between climate and decisions is given by SST Granger causing prices.

For squid, a bivariate test from [3] shows that boats Granger cause SST. The bivariate test statistic Xs-b in Table V has a χ^2 distribution and is based on a ratio of restricted and unrestricted sums of squared residuals from a bivariate VAR of boats and SST. The restrictions exclude boats as explanatory variables for SST and are rejected for squid at the 5% significance level. Since fishing vessels are not physically causing SST, this test result is explained by forward-looking behavior and shows that expectations about future conditions are a significant link between squid harvesters and climate. Therefore, results from the VAR analysis distinguish between three distinct economic linkages between climate fluctuations and decisions about fishing effort: one is an immediate direct effect on effort, the second is an immediate indirect effect on prices, and the third is expectations about future SST.

4. A STRUCTURAL FISHERIES MODEL

The model in this article is similar to Rosenman's [10] open access case, but includes catch prices and climate. Given a catch-effort coefficient A_t, individual fishing effort b_t produces catch, $h_t = A_t b_t$. The catch-effort coefficient A_t depends on crowding externalities, caused by aggregate fishing effort B_t, and stock abundance measured by N_t. In addition, A_t depends on real catch prices P_t, so that h_t may be interpreted in terms of catch revenues.[11] The marginal cost of supplying fishing effort is constant and equal to $\bar{w}$. Individuals treat A_t exogenously, or as determined independently from their decisions, and assume that the variables determining it are related by

$$A_t = (f_0 - \bar{w}) + f_1 B_t + f_2 N_t + f_3 P_t. \quad (1)$$

The f_j are parameters that measure effects on the catch-effort coefficient. The parameter f_1 measures effects of static crowding externalities among fishing vessels, f_2 measures effects of stock abundance and provides a link for the dynamic

[11] An earlier version of this article multiplied catch prices by the catch-effort coefficient, instead of the additive relationship in (1). In this case, decisions about fishing effort depend on the covariance between catch prices and the components of the catch-effort coefficient including climate fluctuations. However, when the catch-effort coefficient depends on stock abundance, the decision rules derived under this type of covariance structure are not stationary and do not adhere to the certainty equivalence principle.

externality related to current fishing effort affecting future stocks, and f_3 measures effects of catch prices or marginal revenues. The presentation of the model below abuses notation by reinterpreting the intercept term f_0 net of $\bar{w}$.

A relationship between aggregate fishing effort and stock abundance is an essential component of a dynamic fishery model, and a necessary link for stock-effort externalities. This article uses a linear stock-effort relationship,

$$N_t = g_0 + g_1 B_t - g_1 g_2 B_{t-1} + g_2 N_{t-1} + X_t. \tag{2}$$

The g_j are parameters that measure effects on stock abundance. The parameter g_1 measures effects of fishing effort on stock abundance. The parameter g_2 measures recruitment or net growth of births less natural mortality and has an absolute value of less than 1. The presence of lagged fishing effort with coefficient $g_1 g_2$ in (2) is a matter of technical convenience that will become apparent. The X_t are an exogenous stochastic process that affects stock abundance and depends on climate.

Due to data constraints, the model treats stock abundance as an unobserved variable.[12] The operator E_t is the expectation of the adjacent expression conditional on $\mathcal{I}_t$, the information set available to decision makers at time t. In general, $\mathcal{I}_t$ contains all variables in the model dated t or earlier. Under the rational expectations hypothesis, these conditional expectations may be interpreted as optimal predictors of date $t + j$ variables conditional on the set of information available at date t, $\mathcal{I}_t$. For empirical work, decision rules that are linear functions of elements in the information set $\mathcal{I}_t$ are convenient. Optimal linear decision rules are obtained by replacing the conditional expectations operators in what follows with the corresponding linear least-squares projections on $\mathcal{I}_t$, $\widehat{E}_t$.

To derive explicit decision rules from the structural fisheries model, further assumptions on the stochastic processes for P_t and X_t are necessary. A set of assumptions consistent with the results of Section 3 are a first-order Markov process for SSTA,

$$S_t = \rho_1 S_{t-1} + \epsilon_{st}, \tag{3}$$

and another for unobservable disturbances to stock abundance,

$$Y_t = \lambda_1 Y_{t-1} + \epsilon_{yt}, \tag{4}$$

to form the process $X_t = \tau S_t + Y_t$. The parameter τ measures the sensitivity of stock abundance to SSTA. The structural fisheries model is closed by assuming that catch prices are generated by a first-order stochastic process which depends on SSTA,

$$P_t = \phi_1 P_{t-1} + \phi_2 S_{t-1} + \epsilon_{pt}. \tag{5}$$

In these equations, the ϵ_{it} are least-squares residuals, each with finite variance and zero conditional mean $\widehat{E}_{t-1}\epsilon_{it} = 0$. Although this specification allows arbitrary contemporaneous correlation between the ϵ_{it}, it does rule out autocorrelation and other types of covariance at nonzero lags.

[12]Future work could treat stock assessments as observed variables for Chinook and sablefish. Including stock assessments as part of the information sets held by fishing vessel operators may not be realistic; an important issue between fisherman and biologists is due to the belief by the fisherman that the stock assessments are often seriously flawed. In light of these issues, stock dynamics in (2) are interpreted at the level of individual decision makers as unobserved variables that represent simplified or local approximations of their true beliefs.

The dynamics of P_t and S_t are transformed into a first-order vector Markov process by defining $z_t' = (P_t, S_t)$, $\epsilon_{zt}' = (\epsilon_{pt}, \epsilon_{st})$, $c_p = (1, 0)$, $c_s = (0, 1)$, and a dynamic transition matrix Φ such that (3) and (5) are equivalent to

$$z_t = \Phi z_{t-1} + \epsilon_{zt}. \tag{6}$$

Assumptions made above require that P_t and S_t be of exponential order less than $1/\beta$, which implies that the eigenvalues of Φ are also less than $1/\beta$ in absolute value.

4.1. *VAR Equations with Nonzero Adjustment Costs*

Given positive dynamic adjustment costs $r > 0$, a discount factor $0 < \beta < 1$, and a stochastic process A_t of order less than $1/\beta$, individual decision makers are assumed to maximize the expected present value of fishing effort,

$$E \sum_{t=0}^{\infty} \beta^t \left(A_t b_t - \frac{r}{2}(b_t - b_{t-1})^2 \right). \tag{7}$$

Technically, solutions to this maximization problem are functions that describe the dynamic allocation of fishing effort and map elements of the model's underlying probability space to sequences of nonnegative real numbers.

Functions that maximize (7) are characterized by first-order necessary conditions, or stochastic Euler equations,

$$r\beta E_t b_{t+1} - r(1+\beta) b_t + r b_{t-1} + A_t = 0, \tag{8}$$

and the stochastic transversality condition,

$$\lim_{T\to\infty} \beta^T E_t b_{t+T} = 0. \tag{9}$$

The Euler equations and transversality condition are necessary and sufficient for maximizing (3).

Appendix A defines constants θ_p, θ_s, and δ_i, $i = 1, 2, 3$, in terms of the structural parameters β, Φ, r, f_i, and g_i, $i = 1, 2$, and shows that optimizing decisions about fishing effort with nonzero adjustment costs follow the rule

$$\begin{aligned} B_t = {} & (1-\lambda_1)\left(\frac{f_0(1-g_2) + f_2 g_0}{\beta r(\delta_2 - 1)}\right) \\ & + (\delta_1 + \delta_3 + \lambda_1) B_{t-1} - (\delta_1\delta_3 + \delta_1\lambda_1 + \delta_3\lambda_1) B_{t-2} \\ & + \delta_1\delta_3\lambda_1 B_{t-3} + \left(\frac{f_3}{\beta r}\theta_p(\Phi - (\lambda_1 + g_2)I) + \frac{\tau f_2}{\beta r}\theta_s\right) z_{t-1} \\ & + \frac{\lambda_1 f_3 g_2}{\beta r}\theta_p z_{t-2} + U_t. \end{aligned} \tag{10}$$

This equation shows restrictions that rationality and optimizing behavior place on the model. Specifically, Appendix A shows that $E_{t-1}U_t = 0$, and the disturbance term U_t in (10) is a forecast error that is optimal or rational in the sense of being uncorrelated with all information in the model dated $t-1$ or earlier. In other words, under the rational expectations hypothesis, statistically optimal forecasts of future catch prices and SST determine fishing effort, and decision makers do not systematically waste information. Equations (3), (5), and (10) form a trivariate VAR for the fisheries model with nonzero adjustment costs. An unrestricted third-order trivariate VAR is the lowest order system that includes all variables in these equations. Consequently, the restrictions in (3), (5), and (10) are tested against an alternative unrestricted third-order trivariate VAR. The first- and second-order VARs in Section 3 may also be interpreted as restrictions of these third-order VARs.

4.2. *VAR Equations with Zero Adjustment Costs*

With zero adjustment costs $r = 0$, maximization of (3) makes sense only if $EA_t = 0$ at each t. A justification for this zero-profits condition is that entry occurs until the expected value of profits equals zero. In this case, any dynamic allocation of fishing effort trivially maximizes (3). Zero profits equilibria are frequently analyzed in fisheries models on the grounds that fisheries are often considered to be open-access resources. H. S. Gordon developed the economic theory of the open-access fishery, and the Gordon–Schaefer model could be called the traditional fisheries model. The Gordon–Schaefer model assumes a logistic or parabolic catch-effort relationship, and that costs are proportional to fishing effort. Similarly in this article, the catch-effort relationship in (1) is parabolic and costs are also proportional to fishing effort. Therefore, the fisheries model with zero adjustment costs in this article appears to be a reasonable representation of the Gordon–Schaefer model and the traditional unregulated fishery, even though logistic growth of fish stocks is not assumed.

In the model with zero adjustment costs, expected profits of zero are guaranteed by realized profits of zero:

$$f_0 + f_1 B_t + f_2 N_t + f_3 P_t = 0. \tag{11}$$

In this case, Appendix B shows that decisions about fishing effort follow the rule

$$\begin{aligned} B_t = {} & (\lambda_1 - 1)\left(\frac{f_0(1-g_2) + f_2 g_0}{f_1 + f_2 g_1}\right) \\ & + (\lambda_1 - g_2) B_{t-1} + \lambda_1 g_2 B_{t-2} + \\ & + \frac{f_3(\lambda_1 - \phi_1 + g_2)}{f_1 + f_2 g_1} P_{t-1} - \frac{\lambda_1 f_3 g_2}{f_1 + f_2 g_1} P_{t-2} \\ & + \frac{\tau f_2(\lambda_1 - \rho_1) - \phi_2 f_3}{f_1 + f_2 g_1} S_{t-1} + V_t. \end{aligned} \tag{12}$$

Equations (3), (5), and (12) form a trivariate VAR for the fisheries model with zero adjustment costs. Since $E_{t-1} V_t = 0$, the disturbance term V_t in (12) is a rational forecast error which coincides with the interpretation of U_t in (10). An important difference in these equations is that B_{t-3} does not appear on the right-hand side of (12), which is a direct consequence of assuming $r = 0$. Other important differences are that S_{t-2} does not appear in (12), and neither does the discount factor β. An unrestricted second-order trivariate VAR is the lowest order system that includes all variables in (3), (5), and (12). However, the restrictions of the model with zero adjustment costs are tested against an alternative unrestricted third-order trivariate VAR for direct comparison of test results from the model with nonzero adjustment costs.

5. RESULTS FOR THE FISHERIES MODEL

This section reports maximum likelihood estimates and likelihood ratio statistics for the fisheries model with nonzero and zero adjustment costs. Appendix C describes maximum likelihood estimation and testing. The model with nonzero adjustment costs is described by (3), (5), and (10) and is represented by a constrained third-order VAR with several zero coefficients and nonlinear cross-equation parameter restrictions from optimizing behavior and rational expectations. The zero adjustment cost version is described by (3), (5), and (12) and is represented by a constrained third-order VAR with several zero coefficients and nonlinear cross-equation parameter restrictions from zero profits and rational expectations. With the methodology described in Appendix C, the constraints that characterize the fisheries model with nonzero and zero adjustment costs may be tested as restrictions of a general third-order VAR.[13]

Table VI presents parameter estimates for the fisheries model with nonzero and zero adjustment costs. The discount factor plays a role in the model with nonzero adjustment costs, and this case is analyzed with the restriction that $\beta = 0.95$. Estimation of the fisheries model uses data that are differences from means and trends; therefore constant terms, including f_0 and g_0, are dropped from (3), (5), (10), and (12).

In Table VI, the parameter f_1 measures crowding externalities among fishing vessels, and estimated values are negative in all regressions except albacore and squid with zero adjustment costs. The parameter f_2 measures effects of stock abundance on catch per unit effort, and estimated values are positive. The parameter f_3 measures effects of catch prices on revenues, and estimated values are positive. The parameter g_1 measures effects of fishing effort on stock abundance, and estimated values are negative. The parameter g_2 measures effects of past stocks on current

[13]Results in Section 3 use first- and second-order VARs to describe dynamics. The discussion and results in Section 3 justify the use of third-order VARs as alternatives to the structural fisheries model and the lower order representations of SSTA and catch prices in (3) and (5).

TABLE VI
Parameter Estimates for the Structural Fisheries Model

	Albacore		Chinook		Sablefish		Squid	
Parameter	$r \neq 0$	$r = 0$	$r \neq 0$	$r = 0$	$r \neq 0$	$r = 0$	$r \neq 0$	$r = 0$
f_1	−0.570	0.003	−0.468	−0.360	−0.869	−0.214	−4.064	−0.113
f_2	1.072	1.166	0.906	0.866	1.209	1.160	1.867	0.876
f_3	0.267	0.598	0.396	0.862	0.360	0.617	0.621	1.691
g_1	−1.071	−0.489	−0.967	−0.881	−1.382	−0.714	−4.129	−0.623
g_2	0.166	0.236	0.443	−0.015	0.096	−0.109	0.941	0.207
r	1.004	0.000	1.158	0.000	0.628	0.000	0.480	0.000
ϕ_1	0.222	0.364	0.809	0.778	0.895	0.897	0.366	0.369
ϕ_2	0.433	0.290	−0.317	−0.735	−0.299	−0.310	0.647	0.639
ρ_1	−0.246	−0.226	−0.227	−0.235	−0.197	−0.204	−0.194	−0.189
λ_1	−0.443	−0.038	−0.029	0.847	0.108	0.081	−0.230	0.930
τ	0.503	1.334	−0.376	−0.659	0.041	−1.151	1.795	−2.116

abundance, and estimated values are positive in all regressions except Chinook and sablefish, with zero adjustment costs.

In Table VI, the parameter ϕ_1 measures autocorrelation in catch prices, and estimated values are positive. The parameter ϕ_2 measures effects of past SST on catch prices, and estimated values are positive for albacore and squid but negative for Chinook and sablefish. The parameter ρ_1 measures autocorrelation in SST, and estimated values are negative and similar in all regressions except for squid, with nonzero adjustment costs. The parameter λ_1 measures autocorrelation in the unobserved disturbance terms, and estimated values vary widely across fisheries.

The parameter τ measures effects of SSTA on stock abundance, and estimated values are positive for albacore and negative for Chinook, with both nonzero and zero adjustment costs. On the other hand, for sablefish and squid, estimated values for τ are positive with nonzero and negative with zero adjustment costs. Consequently, the estimated net effects of a positive SSTA on the Monterey Bay albacore fishery are unambiguously positive because stock abundance and catch prices both increase. In contrast, the net effect of a positive SSTA on the Monterey Bay Chinook fishery is unambiguously negative because abundance and prices both decrease. The estimated net effect of a positive SSTA on sablefish and squid harvesters depends on whether adjustment costs are significantly different from zero, which is addressed next.

Table VII presents the estimated covariance for the structural model and the unrestricted third-order VARs for each fishery. In Table VII, BB refers to the variance of boats, BP is covariance of boats and prices, BS is covariance of boats and SST, PP is variance of prices, PS is covariance of prices and SST, and SS is variance of SST. The final column of Table VII gives the determinant of the estimated covariance matrix. The covariance estimates are generally close for the fisheries model, with both nonzero and zero adjustment costs, but different from those of the third-order VAR. Differences in the covariance estimates imply differences in the determinants of each covariance matrix, and the statistical significance of these differences tests relative likelihoods of the fisheries model with nonzero and zero adjustment costs.

Results from the fisheries model are compared to results from unrestricted third-order VARs with the two likelihood ratio tests described in Appendix C. The first test is based on the asymptotic distribution of the test statistic, while the second test accounts for small sample bias. Both test statistics have χ^2 distributions with degrees of freedom equal to the number of restrictions imposed by the fisheries model on the alternative VAR.[14] Table VIII presents results from the two χ^2 likelihood ratio tests.

The asymptotic test for albacore rejects the model with both nonzero and zero adjustment costs at 5% significance levels, but the small sample test does not. Test results for albacore do not clearly distinguish between nonzero and zero adjustment

[14]Since the number of lags is three in the alternative VAR, $T = 16$ in the first test. The second test controls for the number of estimated parameters in the alternative third-order VAR, and $K = 9$ parameters in each equation. The degree of freedom in each test depends on the two models being compared. The third-order VAR has 27 estimated coefficients. There are 11 estimated parameters with nonzero adjustment costs, and one less or 10 with zero adjustment costs. Therefore, the test statistic for nonzero adjustment costs has 16 degrees of freedom, and the statistic for zero adjustment costs has 17.

TABLE VII
Estimated Covariance of All Models

Model	BB	BP	BS	PP	PS	SS	Det.
Albacore							
$r \neq 0$	0.050	0.082	0.065	1.221	0.017	0.441	0.019
$r = 0$	0.068	0.133	0.096	1.195	0.050	0.440	0.018
T.O. Alt.	0.015	−0.034	0.017	0.491	−0.198	0.200	0.001
Chinook							
$r \neq 0$	0.178	0.472	−0.045	16.781	−0.439	0.285	0.737
$r = 0$	0.191	0.721	−0.058	16.507	−0.436	0.285	0.697
T.O. Alt.	0.079	0.123	0.012	8.276	−0.028	0.196	0.124
Sablefish							
$r \neq 0$	0.438	0.253	0.194	0.288	0.142	0.285	0.012
$r = 0$	0.441	0.250	0.198	0.288	0.142	0.285	0.012
T.O. Alt.	0.113	0.111	0.078	0.156	0.069	0.112	0.000
Squid							
$r \neq 0$	131.150	−0.893	2.647	0.142	0.090	0.285	2.623
$r = 0$	130.305	−0.893	2.621	0.142	0.089	0.285	2.622
T.O. Alt.	115.281	−0.189	1.497	0.089	0.052	0.121	0.694

costs, but significance levels for zero adjustment costs are larger. The estimate of $f_1 > 0$ in Table VI for albacore with zero adjustment costs casts some doubt on this version of the model, but the estimate in this case is small and not significant.[15] The small sample test for Chinook also does not clearly distinguish between nonzero and zero adjustment costs. However, significance levels for zero adjustment costs are larger, and the asymptotic test for Chinook only marginally rejects the model with zero adjustment costs at the 5% level. The asymptotic test for sablefish rejects

[15]Many of the parameters in Table VI are not significant at levels below 5%. Exceptions (with significance levels in parentheses) in the case of zero adjustment costs are ϕ_1 (0.000) and λ_1 (0.000) for Chinook, ϕ_1 (0.000) for sablefish, and ϕ_1 (0.014) and ϕ_2 (0.003) for squid. The test for significance in these cases uses a likelihood ratio statistic similar to the one described in Appendix C. However, in this case, there is a single restriction under the null hypothesis with the relevant parameter set equal to zero in the zero adjustment cost version of the model. The likelihood value under the null hypothesis is compared to the alternative likelihood value from the unrestricted zero adjustment cost version of the model.

TABLE VIII
Tests of the Structural Fisheries Model

	Albacore		Chinook		Sablefish		Squid	
Test	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Asymptotic χ^2								
$r \neq 0$	51.353	0.000	28.556	0.027	58.903	0.000	119.639	0.000
$r = 0$	50.622	0.000	27.660	0.049	59.250	0.000	119.630	0.000
Small sample								
$r \neq 0$	22.467	0.129	12.493	0.709	25.770	0.057	52.342	0.000
$r = 0$	22.147	0.179	12.101	0.794	25.922	0.076	52.338	0.000

the model with both nonzero and zero adjustment costs. The small sample test for sablefish also does not clearly distinguish between nonzero and zero adjustment costs. However, significance levels for the model with zero adjustment costs are larger, and the small sample test marginally misses rejecting the model with nonzero adjustment costs at the 5% level. Tests for squid reject the model with both nonzero and zero adjustment costs.

With estimates of τ in Table VI, interpreting test results from Table VII as favoring models with zero adjustment costs for albacore, Chinook, and sablefish implies that SSTA have relatively strong positive effects on the abundance of albacore, and negative effects on Chinook and sablefish. Since estimated effects on prices and stock abundance have the same sign, a positive SSTA has unambiguously positive effects on albacore and unambiguously negative effects on Chinook and sablefish fisheries. In addition, for Chinook and sablefish, estimates of $g_2 < 0$ in Table VI imply oscillatory stock dynamics.

6. DISCUSSION

In response to the dramatic growth in the U.S. fishing fleet that followed the Magnuson Act, the National Marine Fisheries Service (NMFS) and other management agencies have called for quantitative economic analyses to guide and support their policies. Climate fluctuations, including ENSO, are a driving force in Pacific fisheries. This article analyzes the effects of fluctuations in sea surface temperatures and catch prices on fishing effort in four important fisheries of Monterey Bay, California: albacore tuna, Chinook salmon, sablefish, and squid.

The VAR analysis in this article identifies three distinct links between fishing effort and climate. The first link is the direct effect of climate on fishing effort. The second link is the effect of climate on catch prices. The third link is the effect of observed climate on expectations about future climate. All three links ultimately influence decisions about fishing effort. Results from the VAR analysis show that the first and second links are significant for albacore, Chinook, sablefish, and squid. Results also show that the third link is significant for squid.

The VAR results on the first climate link suggest that the effects of sea surface temperatures on fishing effort may be pervasive. These results do not support Rosenman's [11] analysis of Atlantic mackerel, which shows no significant effects from climate. Like squid, mackerel are an open water nearshore schooling species, or coastal pelagic, and their abundance is thought to be affected by SSTs. Rosenman's analysis uses sea bottom temperatures to represent climate, which could explain the discrepancy in results. In addition, VAR results in this article on the second climate link do not support Rosenman's assumptions of price-climate exogeneity. In particular, the significant relationships between SSTs and catch prices reported in this article could indicate bias in Rosenman's results for mackerel.

The focus of NMFS work on ENSO has been changes in species abundance, which most closely corresponds to the first link between climate and fishing effort identified by the VAR analysis. The second link is important to managers because it demonstrates that climate affects fisheries through mechanisms other than local abundance, including decisions about fishing effort through effects on catch prices. Results for the third link demonstrate that climate can also affect fisheries through forward-looking behavior by harvesters. Forward-looking behavior may be represented as expectations about future climate but not necessarily as rational expectations, which Rosenman assumes in his analysis of mackerel.

In decisions about fishing effort, forward-looking behavior has important policy implications for fisheries managers. The National Oceanic and Atmospheric Administration (NOAA), NMFS parent agency, has a program to evaluate the economic effects of its long-range climate forecasts, including ENSO. Results from the VAR analysis imply that these forecasts, if taken seriously, could significantly affect catch prices and fishing effort. In other words, there is a relationship between the forecasts and the value of each fishery: the value of a forecast depends on the type of forward-looking behavior, but the VAR analysis does not identify the type. In a review of NOAA's program to evaluate climate forecasts, the National Research Council [9] encourages the use of structural models to empirically analyze forward-looking behavior and to test the rational expectations hypothesis. This article develops a fisheries model to provide a structural interpretation of results from the VAR analysis and test the rational expectations hypothesis.

The dynamic linear rational expectations fisheries model in this article provides a structural interpretation of the complex relationships between climate, catch prices, and fishing effort. This article estimates and tests the fisheries model with nonzero and zero dynamic adjustment costs. Test results do not clearly distinguish between nonzero and zero adjustment costs but appear to favor the model with zero adjustment costs for albacore, Chinook, and sablefish. Test results for squid reject the model with both nonzero and zero adjustment costs, which is worth pointing out for two reasons. First, the squid fishery is the least regulated of the fisheries analyzed in this article. Second, the VAR analysis in this article shows evidence of forward-looking behavior by squid harvesters but not of rational expectations.

Estimation results show that crowding externalities among fishing vessels decrease catch per unit effort for Chinook and sablefish, which motivates regulation of these fisheries. Estimation results also show that catch per unit effort increases with stock abundance for each fishery analyzed in this article. However, results also show that abundance responds negatively to fishing effort, and this feedback is the source of a dynamic externality that motivates regulation. Estimated effects of climate on species abundance in this article agree with results from NMFS and show that the effects of ENSO on abundance in Monterey Bay are positive for albacore and negative for Chinook, sablefish, and squid. However, ENSO also affects catch prices, and net effects depend on how both prices and abundance respond. Results for the model with zero adjustment costs show that net effects of ENSO are unambiguously positive for albacore and unambiguously negative for Chinook and sablefish. Results for Chinook and sablefish also imply oscillatory stock dynamics that could be a confounding factor in the management of these fisheries.

Results for effects of ENSO on species abundance highlight important structural relationships that are clarified by the fisheries model in this article. The VAR analysis includes relationships between SSTs and fishing effort, but it does not directly provide results for abundance. On the other hand, the fisheries model includes a structural relationship between SSTs and stock abundance. Since this article treats fish stocks as unobserved variables, the fact that results from empirical work with the fisheries model agree with NMFS is more than reassuring; it gives credibility to structural economic modeling and the analysis of economic behavior as important tools for understanding relationships between fisheries and climate.

The rational expectations hypothesis implies a set of cross-equation restrictions on the model that are tested in this article. Results from these tests support rational expectations by commercial trollers for albacore and Chinook, by trawlers for sablefish, but not by the purse seiners harvesting squid. The test results that support rational expectations have important policy implications and provide evidence to NOAA that long-range information about ENSO and other climate fluctuations has significant value for these fisheries. The test results also imply regulations that allow fishing vessel operators the freedom to allocate their effort in response to climate, and catch price variability may be most efficient for maximizing the value of climate information. Moreover, designing policy based on rational expectations could allow fisheries managers to reduce the overall economic costs of landing a given level of catch. However, designing cost-effective or net benefit-maximizing policies would necessarily involve extensions of the work in this article, including an analysis of potentially important interactions between fisheries.

Further research could extend the work presented in this article in several interesting and important directions. A number of simplifying assumptions in this article about stock dynamics, autoregressive lag lengths, catch price exogeneity, and other factors deserve further attention. These extensions could increase confidence in the results presented in this article for albacore, Chinook, and sablefish and perhaps provide a statistically acceptable model of squid harvesting. Results in this article also abstract from important determinants of fishing effort, including decisions about vessel capacity and gear type. Work on these topics could use data from the Fisheries Economics Data Program, recently begun by the Pacific States Marine Fisheries Commission. The structural fisheries model in this article could be used to analyze efficient policies, along the lines of Rosenman's [10] work on optimal fisheries management, except in an empirical context. A top priority for future research is empirical work that includes policy data, including information on total allowable catch, season length, trip limits, entry limitations, or other instruments in the wide array used for fisheries management. Policy regime shifts in fisheries management, including the Magnuson Act, also provide a number of valuable natural experiments to target for analysis.

The type of analysis in this article could also be applied on a wider geographical scale or to fisheries in other locations. On the other hand, applying the type of analysis in this article to longer time series could give deeper insights into fisheries-climate linkages, including the effects of fluctuations that occur on interdecadal scales, such as the Pacific Decadal Oscillation [6]. Applying the analysis in this article to longer time series would contribute an important economic dimension to the growing body of work on fishery-climate interactions that has mainly focused on fisheries ecology. Integrating the work and extensions in this discussion with related work in fisheries ecology and climate modeling is essential to the future success of fisheries management. This success also depends on an improved understanding of the complex biological and economic linkages between fisheries. The economic linkages could be analyzed by extending the structural fisheries model in this article along the lines of the multifactor models by Hansen and Sargent [4]. Fishing vessel operators tend to focus their effort on groups of species, or fleet configurations, which depend on vessel and gear type. For example, trollers in Monterey Bay fish for albacore, Chinook, crab, and various species of rockfish, depending on availability and prices. Another class of vessels with purse seines targets coastal pelagics, including anchovy, mackerel, sardine, and squid.

The California sardine stock recently surpassed 1 million tons for the first time since the heyday of Monterey's Cannery Row in the 1940s and is now considered fully recovered. At its peak around 1936, the California sardine fishery landed about 800,000 tons, and the stock is estimated to have been more than 3.5 million tons. A combination of unfavorable climate and overfishing led to a steady decline in abundance, resulting in a moratorium on sardine harvesting from 1974 to 1986. Because it is an important food source for salmon and other species, the collapse of the sardine fishery demonstrates important biological and economic linkages in fisheries management. The reemergence of the California sardine fishery was met by the Pacific Fishery Management Council with an innovative regulatory strategy that indexes total allowable catch by SSTs. This new climate-based policy for the sardine fishery went into effect on January 1, 2000.[16] The new policy raises several important management issues involving linkages between fisheries, including the effects on predatory species like salmon, interactions with other regulated fisheries such as mackerel, and unregulated species like squid. To address these issues, empirical work using a multispecies version of the fisheries model in this article, extended along the lines of this discussion, could provide a reliable source of quantitative economic information for fisheries managers.

APPENDIX A: NONZERO ADJUSTMENT COSTS

Lagging (8) one period and using the lag operator L shows that the Euler equations are equivalent to

$$(1-L)(1-\frac{1}{\beta}L)b_t = -\frac{1}{\beta r}A_{t-1}. \tag{13}$$

These equations are decision rules for fishing effort in terms that are exogenous to individuals' decisions including externalities. Since the model treats stock abundance as an unobserved variable, stock dynamics are expressed as

$$(1-g_2L)N_t = g_0 + g_1(1-g_2L)B_t + X_t. \tag{14}$$

Substituting for N_t in (1) gives

$$(1-g_2L)A_t = (1-g_2L)(f_0+f_1B_t+f_3P_t) + f_2(g_0+g_1(1-g_2L)B_t+X_t). \tag{15}$$

Multiply the right-hand side of (13) by $(1-g_2L)$ and aggregate over individuals by replacing b_t with B_t. Then lag (15) one period, substitute this expression into (13), and collect endogenous fishing effort terms to obtain

$$\begin{aligned}(1-g_2L)\left((1-L)\left(1-\frac{1}{\beta}L\right)+\frac{f_1+f_2g_1}{\beta r}L\right)B_t \\ = -\frac{f_0(1-g_2)+f_2g_0}{\beta r} - \frac{f_3}{\beta r}(1-g_2L)P_{t-1} - \frac{f_2}{\beta r}X_{t-1}.\end{aligned} \tag{16}$$

In this equation, the endogenous fishing effort terms are collected on the left-hand side while the exogenous catch prices and stock productivity terms appear on the

[16]Richard Parrish, Pacific Fisheries Environmental Laboratory (personal communication).

right. The left-hand side of (16), with a real variable z replacing the lag operator L, defines the characteristic equation of this system.

With no further restrictions on stock dynamics other than those imposed by (2), the characteristic equation,

$$(1 - g_2 z)\left(\frac{1}{\beta} z^2 + \left(\frac{f_1 + f_2 g_1}{\beta r} - \frac{1+\beta}{\beta}\right) z + 1\right) = 0, \tag{17}$$

is cubic and may be factored as $(1 - \delta_1 z)(1 - \delta_2 z)(1 - \delta_3 z) = 0$. With $\delta_3 = g_2$, this factorization reduces to δ_1 and δ_2, being, respectively, the negative and positive roots of

$$\delta^2 - \left(\frac{1+\beta}{\beta} - \frac{f_1 + f_2 g_1}{\beta r}\right)\delta + \frac{1}{\beta} = 0. \tag{18}$$

The factorization $(1 - \delta_1 L)(1 - \delta_2 L)(1 - \delta_3 L)B_t$ replaces the left-hand side of (16). Since $\delta_2 > 1$, divide both sides of this equation by $(1 - \delta_2 L)$ to obtain the forward solution of the system. Applying

$$(1 - \delta_2 L)^{-1} = -\frac{\delta_2^{-1} L^{-1}}{1 - \delta_2^{-1} L^{-1}} \tag{19}$$

to the right-hand side of (16) equals

$$\sum_{j=0}^{\infty} \delta_2^{-j} \left(\frac{f_0(1 - g_2) + f_2 g_0}{\beta r} + \frac{f_3}{\beta r}(1 - g_2 L) P_{t+j} + \frac{f_2}{\beta r} X_{t+j}\right), \tag{20}$$

so that

$$\begin{aligned} B_t = {} & \frac{f_0(1 - g_2) + f_2 g_0}{\beta r(\delta_2 - 1)} + (\delta_1 + \delta_3) B_{t-1} - \delta_1 \delta_3 B_{t-2} \\ & + \frac{1}{\beta r} \sum_{j=0}^{\infty} \delta_2^{-j} (f_3 (1 - g_2 L) E_t P_{t+j} + f_2 E_t X_{t+j}). \end{aligned} \tag{21}$$

This equation shows that the endogenous dynamics of fishing effort follow a process that depends on a forward geometric distribution of conditional expectations for exogenous catch prices and stock productivity.

Let Γ denote the diagonal matrix of eigenvalues for Φ from (6). Then Φ may be decomposed into Γ, its matrix of eigenvectors G, and the inverse G^{-1}, by $\Phi = G\Gamma G^{-1}$. Then the rational or optimal j-step ahead linear forecasts of catch prices, for example, are

$$\widehat{E}_t P_{t+j} = c_p E_t z_{t+j} = c_p G \Gamma^j G^{-1} z_t. \tag{22}$$

This expression shows how rational expectations depend on the geometric distribution

$$G\left(\sum_{j=0}^{\infty} (\delta_2^{-1} \Gamma)^j\right) G^{-1} z_t. \tag{23}$$

Since $\delta_2 = 1/(\delta_1 \beta)$, and P_t and S_t are of exponential order less than $1/\beta$, $|\gamma_i/\delta_2| = |\gamma_i \delta_1 \beta| < 1$. Therefore, the series in (23) converges to a diagonal matrix with nonzero components given by $1/(1 - \delta_2^{-1}\gamma_i)$. Denote the limiting matrix by

Γ_δ, and the matrix products $\theta_p = c_p G \Gamma_\delta G^{-1}$ and $\theta_s = c_s G \Gamma_\delta G^{-1}$. Let $\theta_y = 1/(1 - \delta_2^{-1}\lambda_1)$. Then, (21) may be rewritten as

$$B_t = \frac{f_0(1-g_2)+f_2 g_0}{\beta r(\delta_2 - 1)} + (\delta_1+\delta_3)B_{t-1} - \delta_1\delta_3 B_{t-2} + \left(\frac{f_3}{\beta r}\theta_p + \frac{\tau f_2}{\beta r}\theta_s\right)z_t - \frac{f_3 g_2}{\beta r}\theta_p z_{t-1} + \frac{f_2}{\beta r}\theta_y Y_t. \tag{24}$$

Define $\widetilde{Y}_t = (f_2/\beta r)\theta_y Y_t$. Lag (24) and solve for $\widetilde{Y}_{t-1}$ to derive an expression for $E_{t-1}\widetilde{Y}_t = \lambda_1 \widetilde{Y}_{t-1}$. Let I denote the 2×2 identity matrix and define a zero conditional mean disturbance term that is uncorrelated with past information,

$$U_t = \left(\frac{f_3}{\beta r}\theta_p + \frac{\tau f_2}{\beta r}\theta_s\right)\epsilon_{zt} + \widetilde{Y}_t - E_{t-1}\widetilde{Y}_t. \tag{25}$$

Note that $\theta_p z_t = \theta_p(\Phi z_{t-1} + \epsilon_{zt})$ and $\theta_s z_t = \theta_s(\Phi z_{t-1} + \epsilon_{zt})$, so that (24) and (25) are equivalent to (10).

APPENDIX B: ZERO ADJUSTMENT COSTS

Use (14) to substitute for N_t in (11) to derive an expression in terms of fishing effort and exogenous factors:

$$(1 - g_2 L)(f_0 + f_1 B_t + f_3 P_t) + f_2(g_0 + g_1 B_t + X_t) = 0. \tag{26}$$

Rearranging this equation shows how endogenous fishing effort depends on exogenous catch prices and stock productivity:

$$-B_t = \frac{f_0(1-g_2)+f_2 g_0}{f_1 + f_2 g_1} + g_2 B_{t-1} - \frac{f_3 g_2}{f_1 + f_2 g_1}P_{t-1} + \frac{f_3}{f_1 + f_2 g_1}P_t + \frac{f_2}{f_1 + f_2 g_1}X_t. \tag{27}$$

Since $X_t = \tau S_t + Y_t$,

$$-B_t = \frac{f_0(1-g_2)+f_2 g_0}{f_1 + f_2 g_1} + g_2 B_{t-1} - \frac{f_3 g_2}{f_1 + f_2 g_1}P_{t-1} + \frac{f_3}{f_1 + f_2 g_1}P_t + \frac{f_2 \tau}{f_1 + f_2 g_1}S_t + \frac{f_2}{f_1 + f_2 g_1}Y_t. \tag{28}$$

Following the construction in the case of nonzero adjustment costs, summarize the unobserved disturbance terms by $Y_t' = (f_2/(f_1 + f_2 g_1))Y_t$, use (28) to derive an expression for $E_{t-1}Y_t' = \lambda_1 Y_{t-1}'$, and define a conditional mean zero disturbance term that is uncorrelated with past information:

$$V_t = -\left(\frac{f_3}{f_1 + f_2 g_1}\epsilon_{pt} + \frac{\tau f_2}{f_1 + f_2 g_1}\epsilon_{st}\right) + Y_t' - E_{t-1}Y_t'. \tag{29}$$

Replace P_t and S_t with their Markov representations from (3) and (5); then (28) and (29) are equivalent to (12).

APPENDIX C: MAXIMUM LIKELIHOOD ESTIMATION AND TESTING

Define a stacked vector of residuals for the VAR with nonzero adjustment costs (3), (5), and (10) by $u_t' = (U_t, \epsilon_{pt}, \epsilon_{st})$. Assume that u_t has a multivariate normal distribution with zero mean $Eu_t = 0$ and finite covariance matrix $\mathrm{E}u_t u_t' = \Sigma$. The likelihood function for a sample of observations with residuals $\hat{u}_t$, $t = 1, \ldots, T$, is

$$\mathscr{L} = (2\pi)^{-(3/2)T} |\Sigma|^{(1/2)T} \exp\left(-\tfrac{1}{2}\sum_{t=1}^{T} \hat{u}_t' \Sigma^{-1} \hat{u}_t\right). \tag{30}$$

Following [13], the maximum likelihood estimate of Σ is the sample covariance matrix

$$\widehat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t'. \tag{31}$$

Minimize $|\widehat{\Sigma}|$ with respect to each of the model's parameters to get maximum likelihood estimates. Similarly, define a stacked vector of residuals for the VAR with zero adjustment costs (3), (5), and (12) by $v_t' = (V_t, \epsilon_{pt}, \epsilon_{st})$ and assume it has a multivariate normal distribution with zero mean, covariance matrix Ω, and maximum likelihood estimate $\widehat{\Omega}$.

Let $\widehat{\Lambda}$ be the maximum likelihood estimate of Λ, the covariance matrix from an unrestricted third-order VAR, which is less constrained than the fisheries model with either zero or nonzero adjustment costs. The likelihood ratio statistics defined by $T(\log|\widehat{\Sigma}| - \log|\widehat{\Lambda}|)$ and $T(\log|\widehat{\Omega}| - \log|\widehat{\Lambda}|)$ have asymptotic χ^2 distributions. The degrees of freedom for each statistic equal the number of restrictions imposed by the model on the third-order VAR. A small sample variation of these statistics replaces T, the number of data points in the sample after conditioning for lags, with $T - K$, where K is equal to the number of estimated parameters in each equation of the unrestricted VAR [3].

APPENDIX D: NOMENCLATURE

A_t	catch-effort coefficient at time t
b_t, B_t	individual and aggregate fishing effort at t
N_t	stock abundance at t
P_t	catch price at t
S_t	sea surface temperature anomaly at t
f_1	effect of aggregate fishing effort on catch per unit effort
f_2	effect of stock abundance on catch per unit effort
f_3	effect of catch prices on revenue per unit effort
g_1	effect of fishing effort on stock abundance
g_2	effect of stock recruitment on abundance
r	effect of dynamic adjustment costs
β	discount factor
ϕ_1	autocorrelation in catch prices
ϕ_2	effect of sea surface temperature anomaly on catch prices
λ_1	autocorrelation in unobserved disturbances

ρ_1 autocorrelation in sea surface temperature anomalies
τ effect of sea surface temperature anomaly on stock abundance

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