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Structural Vector Error Correction Modeling of Integrated Sportfishery Data

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Abstract *We demonstrate how to specify and estimate a time series model that can isolate the effects of changes in fishery policy and forecast the outcome of policy changes in the context of changing climate and economic factors. The approach is illustrated with data from the headboat fishery for red snapper in the Gulf of Mexico. The initial data analysis finds that effort and harvest are cointegrated series and that effort appears to respond somewhat to past changes in harvest. This suggested a structural vector error correction model specification. Model estimation results indicate that seasonal closures directly influence both harvest and effort, whereas bag and minimum size limits only affect harvest directly. Also, climate activity has a moderate influence on this fishery, mainly via changes in effort. Model forecasts are evaluated relative to a more naïve specification using out-of-sample data and the use of the model for policy analysis is demonstrated.*

Key words Climate, Gulf of Mexico, red snapper, sportfishing demand, structural vector error correction, time series.

JEL Classification Codes Q22 Q26 Q28 C32.

Introduction

Choosing among competing fisheries rebuilding plans requires an understanding of fishery behavior under different management regimes. The extended time horizon of many rebuilding plans suggests that this understanding can be complicated by the time series characteristics of effort and harvest and the changing conditions outside the fishery (*e.g.*, climate). Therefore, a time series modeling strategy that can measure and forecast the short and long-run outcomes of policy changes within the broader ecosystem would be useful.

There is limited empirical research on the relationships among aggregate effort, harvest, and biomass, especially for sportfisheries. Stevens (1966) was the first to use regression techniques to analyze the effect of changes in biomass levels on sportfishing effort. He estimated a pooled-site aggregate trip demand model that included a measure of biomass among the explanatory variables. Andrews and Wilen (1988) outlined

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a similar approach, but used seasonal proxies because actual biomass indices were not available. However, they added catch rates to examine the effects of changes in average catch on effort in Northern California's for-hire recreational fishing industry. Raab and Steinnes (1980) also used catch rates and total catch proxies to estimate a daily time series model of angler response to changes in angling success. Loomis and Cooper (1990) expanded on this approach by adding economic variables, such as income and travel cost, along with catch (keep) rates in their model of aggregate fishing trip demand for sections of the Feather River in California. Others (*e.g.*, Schuhmann 1998) have parameterized bioeconomic harvest and effort equations for sportfisheries.

None of the aforementioned empirical sportfishery studies addresses the time series properties of fishery data in a systematic way, nor do they examine the long-run behavior within the broader ecosystem and policy setting. With regard to time series properties, failure to test and address series stationarity, for example, could lead to incorrect inference regarding policy effects and inaccurate forecasts. Ignoring the potential outside influences on fishery behavior could mistakenly attribute the affects of factors, such as changing economic and climate conditions, to simultaneously changing policy.

This article formally explores the interrelationship between sportfishing effort and harvest within a managed fishery system, while recognizing the influence of variations in biomass, climate conditions, and key economic variables. We demonstrate how to use formal time series methods to: *(i)* explore the short and long-run relationships between effort and harvest, *(ii)* evaluate the effects of historical regulations in this context, and *(iii)* forecast the effects of policy changes. We also demonstrate the potential consequences of an estimation approach that ignores the time series characteristics of the data.

Our analysis follows similar work on commercial fisheries (Dalton 2001, Dalton and Ralston 2004, Rosenman 1987)[1] in using structural vector autoregression (SVAR) methods to study aggregate effort and harvest in the headboat fishery for red snapper in the Gulf of Mexico (GOM) from 1986 to 2003. However, stationarity and cointegration tests indicate that the structural vector error correction (SVEC) form is a more appropriate representation of effort and harvest in the GOM case study. This exploratory analysis uses a simple angler demand and harvest production specification to further identify model parameters and isolate the effects of historic variations in red snapper regulations in the presence of fluctuations in red snapper biomass and climate conditions. Note, however, a primary goal of the GOM example is to demonstrate the application of SVEC modeling techniques to integrated fisheries data. Also, as we are interested in forecasting, the proxy variables for external fishery influences were selected, in large part, based on the availability of forecasts. The climate indices used are routinely forecasted and available as data series. Future analyses will consider alternative proxies for key model quantities.

An econometric fishery model is presented in the next section followed by a review of the relevant data and an initial analysis of time series properties. A SVEC model for recreational harvest and effort is then introduced, and the results of the estimation are summarized. The article closes with a policy example and discussion.

Model of For-hire Sportfishing

The typical bioeconomic fishery system includes bi-directional feedback among effort and harvest and biomass and harvest. For simplicity, we assume that changes in effort and harvest do not feed back to affect biomass. That is, we assume biomass is exogenously determined outside of the system. This is a realistic assumption for sectors, such as the

[1] Dalton (2001) and Dalton and Ralston (2004) estimated vector autoregression and structural models of the interactions between sea surface temperature, commercial effort, and commercial harvest. Rosenman (1987) used bottom water temperature in a structural time series model of commercial fishing.

case study considered in this article, that make up a relatively small share of the total harvest in a fishery. The system we construct, therefore, consists of equations for the production of aggregate harvest by the for-hire sector and the demand for angler days (trips). The aggregate supply of angler days is assumed to be perfectly elastic. Similar assumptions are implicit in the work of Andrews and Wilen (1988), and our depiction of sportfishing effort and harvest can be considered a generalization and extension of their model.

The aggregate harvest, H_t, by the for-hire sector in month t is assumed to be governed by the following Cobb-Douglas production function:

$$H_t = z_t D_t^{\varphi_{12}} F_t^{g_{11}}, \tag{1}$$

where D_t is aggregate effort measured in terms of angler days, F_t is the stock of fish, φ_{12} and g_{11} are response coefficients, and z_t is the catchability coefficient.[2] The catchability coefficient is assumed to vary in time based on climate patterns, regulations, and unobserved factors:

$$z_t = \exp(\gamma_1 \mathbf{k}_t + \mathbf{g}_{14}\mathbf{r}_t + \mathbf{g}_{15}\mathbf{w}_t + \varepsilon_{1,t}), \tag{2}$$

where $\mathbf{k}_t$ is a vector of deterministics (constant, trend, etc.); $\mathbf{r}_t$ is a vector with variables indicating harvest regulations; $\mathbf{w}_t$ is a vector of variables measuring climatic conditions; γ_1, $\mathbf{g}_{14}$, and $\mathbf{g}_{15}$ are parameter vectors; and $\varepsilon_{1,t}$ is an independent white noise error term. A similar parameterization of the catchability coefficient in a Cobb-Douglas harvest function is shown in Eide *et al*. (2003).

The number of angler days is assumed to be generated according to a demand function for for-hire services:

$$D_t = v_t m_t^{g_{22}} c_t^{g_{23}} E[H_t]^{\lambda}, \tag{3}$$

where c_t is the cost per angler day, m_t is income, $E[H_t]$ is the expected harvest, g_{22} and g_{23} are response coefficients, and v_t is the intercept in the (log-linear) angler day demand equation. The cost and income variables, c and m, are normalized by a price index for a Hicksian composite of all other goods (Alston, Chalfant, and Piggott 2002). The demand intercept is specified as a function of climate patterns, regulations, and unobserved factors:

$$v_t = \exp(\gamma_2 \mathbf{k}_t + \mathbf{g}_{24}\mathbf{r}_t + \mathbf{g}_{25}\mathbf{w}_t + \varepsilon_{2,t}), \tag{4}$$

where γ_2, $\mathbf{g}_{24}$, and $\mathbf{g}_{25}$ are parameters, and $\varepsilon_{2,t}$ is an independent white noise error term. Harvest expectations are assumed to be formed based on aggregate harvest in previous periods as $E[H_t]^{\lambda} = \sum_{i=1}^{p} H_{t-i}^{\lambda a_{i,22}}$. The number of periods in this finite distributed lag process is determined empirically as described in the model specification section below. Note that this is the only "dynamic" portion of the model to this point. This naïve model will serve as the point of departure as we develop a more general time series formulation that allows for additional model dynamics with autoregressive lags in the harvest and effort equations.

In natural logarithms, the more general harvest production and angling demand equations form the following SVAR system:

[2] The somewhat unusual subscripting is used to be consistent with the specification of the econometric model below.

$$\mathbf{\Gamma y}_t = \sum_{i=1}^{p} \boldsymbol{A}_i \mathbf{y}_{t-i} + \mathbf{G}\mathbf{x}_t + \boldsymbol{\gamma}\mathbf{k}_t + \boldsymbol{\varepsilon}_t, \tag{5}$$

where:

$$\mathbf{y}_t = \left[Ln(H_t) \quad Ln(D_t) \right],$$

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & -\varphi_{12} \\ 0 & 1 \end{bmatrix},$$

$$\boldsymbol{A}_i = \begin{bmatrix} a_{i,11} & 0 \\ a_{i,21} & \lambda a_{i,22} \end{bmatrix},$$

$$\gamma = [\gamma_1 \ \gamma_2]$$

$$\mathbf{x}_t = \left[Ln(F_t) \quad Ln(m_t) \quad Ln(c_t) \quad \mathbf{r}_t \quad \mathbf{w}_t \right],$$

$$\mathbf{G} = \begin{bmatrix} g_{11} & 0 & 0 & \mathbf{g}_{14} & \mathbf{g}_{15} \\ 0 & g_{22} & g_{23} & \mathbf{g}_{24} & \mathbf{g}_{25} \end{bmatrix},$$

and

$$\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}_{1,t} \ \boldsymbol{\varepsilon}_{2,t}],$$

with E($\boldsymbol{\varepsilon}_t$)=$0$, E($\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t$)=$\Sigma_\varepsilon$, and E($\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_s$)=$0$ for $t \neq s$ (Breitung, Gruggemann, and Lütkephol 2004). Note that this specification imposes zero restrictions such that trip cost and income do not appear in the harvest equation and abundance does not appear in the angler day demand equation. Also, a measure of expected red snapper harvest is explicit in the angler day equation as lagged harvest, but lagged angler day terms do not appear in the harvest equation. This assumption is examined in the initial data analysis using causality tests. The naïve model is restricted even further, whereby $\alpha_{i,11} - \alpha_{i,21} = 0$.

Before leaving the model discussion, it is worth noting that the long-run relationship between harvest and effort can usually be recovered with an assumption about the functional form of the biomass growth function (Clark 1990). Mkenda and Folmer (2001) show how this derivation suggests that (integrated) harvest and effort series will be cointegrated. We adopt this rational as an important reason for testing for series stationarity and cointegration. However, for the Cobb-Douglas harvest function specified in equation (1), a closed form for the sustainable harvest function does not exist for the typical (*e.g.*, logistic) biomass growth functions (Bjorndal and Conrad 1987). Furthermore, as noted above, we are assuming that the take from the for-hire sportfishing sector modeled in the case study is not large enough to significantly affect biomass levels. In this case the existence of an equilibrium relationship between total for-hire effort and the harvest of one particular species is an empirical question. Our approach, therefore, is to let the data determine both the short and long-run relationship between harvest and effort. In the context of the formal cointegration analysis shown below, the reduced form long-run relationship is summarized in the cointegrating parameter.

Data for Model Application

Fishery

Estimates of aggregate effort and harvest are from the National Marine Fisheries Service (NMFS) Headboat Survey in the GOM.[3] Headboats are passenger vessels that charge per angler for partial or full day fishing trips. The Headboat Survey has been conducted in the GOM since 1986 (Dixon and Huntsman 1983). Although the survey was designed as a census, actual reporting has ranged from 70-99% of estimated total trips.

Headboat operators in the GOM have reported that they spend the majority of their time targeting snappers, especially red snapper (Holland, Fedler, and Milon 1999; Sutton *et al*. 1999). This targeting pattern has persisted since the late 1970s, suggesting that the GOM headboat industry is heavily reliant on snapper (Browder, Davis, and Sullivan 1981; Ditton, Holland, and Gill 1992). Therefore, we expect significant co-movement of the aggregate headboat effort and red snapper harvest series. The headboat sector has historically accounted for a relatively small share of total red snapper harvest in the GOM (NMFS 2005). Thus, it is reasonable to assume that the other components of the GOM red snapper fishery are exogenous with respect to headboat activity.

Weather and climate events have been consistently cited by the headboat industry as a significant problem (Holland, Fedler, and Milon 1999; Sutton *et al*. 1999). Note, however, that problematic weather and climate events could refer to unpredictability or rough conditions. The surveys of headboat operators have not attempted to separate these two definitions. Results from these surveys find that headboat operators in the GOM view information provided by the NOAA Weather Service as moderately to extremely important (Gill and Ditton 1993). This suggests that climate and weather patterns should influence aggregate headboat activity in the GOM.

The GOM red snapper recreational fishery has been actively managed by the GOM Fisheries Management Council since the mid 1980s. According to Ditton *et al*. (2001), "the prospect of zero catch has particularly hurt the business of party boat operators who target primarily snapper and grouper in the western GOM." Table 1 summarizes the historical changes in the recreational bag and minimum size limits and indicates the periods when the fishery was closed. There were a total of sixteen policy interventions over the period of record, including five minimum sizes, four bag limits, and four closed seasons. We interpolated each type of regulation to a monthly time series from 1986 to 2003 as follows: closed seasons appear as the percentage of the month closed; bag and size limits appear as the level active in each month; and months without a bag limit are indicated with *99*. Bag and minimum size limits are weighted by percentage of the month that is closed to sportfishing so that the bag limit is zero in a closed month.

The top two panes of figure 1 show monthly measures of log effort and harvest in terms of headboat angler days (*angday_log*) and harvest of red snapper (*rsland_log*), respectively, in the GOM from 1986 to 2003. There is a clear pattern of seasonality in this fishery, with peak activity in the summer months. Also, there is a noticeable break in red snapper harvest at the start of 1998. According to table 1, this period corresponds with the start of significant red snapper fishery closures and the lowering of the bag limit. The same structural break is not as evident in the headboat angler days because trips to harvest other species could still occur.

The index used to proxy the stock of red snapper is based on the pounds of red snapper biomass estimated in the most recent stock assessment for the Gulf of Mexico (NMFS 2005). Annual estimates of biomass for age classes two through fifteen were totaled, and monthly values were generated via linear interpolation. Ages two and above are thought to comprise the adult population harvested by the recreational sector. Also, prior to the in-

[3] References for all data sources are listed at the bottom of table 2.

creases in the minimum size limit in during the 1990s, more than 70% of the recreational catch was between one and four annually. Following the size limit increases, much less of the recreational harvest was at age one. Furthermore, the headboat sector generally harvests relatively larger, and presumably older, fish. The natural log of the final monthly biomass index is shown in the first graph (*RS_abunda_log*) of the bottom row in figure 1.

Table 1
Changes in Recreational Red Snapper Regulations in the Gulf of Mexico

Year	Size Limit (Inches TL)	Daily Bag Limit (Number of Fish)	Season Length (days)	Allocation (Million Pounds)
1984	13[1]	no bag limit[2]	365	
1990	13	7	365	2.97
1994	14	7	365	1.96
1995	15	5	365	1.96
1996	15	5	365	2.94
1997	15	5	330[3]	2.94
1998	15	4[4]	272[5]	2.94
1999	15[6]	4	240[7]	4.47
2000	16	4	194[8]	4.47
2001	16	4	194	4.47
2002	16	4	194	4.47
2003	16	4	194	4.47

[1] For-hire boats exempted until 1987.
[2] Allowed to keep five undersized fish per day.
[3] Fishery closed on November 27, 1997.
[4] Bag limit was five fish from January through April, 1998.
[5] Fishery closed on September 30, 1998.
[6] Size limit was 18 inches from June 4 through August 29, 1999.
[7] Fishery closed on August 29, 1999.
[8] Fishing season opens at 12:01 a.m. April 21 and closes at 12:00 midnight October 31.

Economic Factors

The NMFS Headboat Survey does not collect information about the price of trips or the incomes of paying passengers. Therefore, we need proxies for these factors to estimate the angler day demand equation in expression (3). Note that, in the time series context, the primary goal of the income and price proxies is to help indentify the angler day demand as distinct from harvest production. Good proxies in this case will influence the angler day demand, but not harvest production. It is also important to have proxies that are regularly forecasted for use in fishery forecasts using this model.

The income variable selected is the monthly U.S.A. per capita disposable income series from the Bureau of Economic Analysis. An income measure for the entire U.S.A. was used because the headboat passengers could have come from anywhere in the country. Furthermore, potentially relevant regional income measures are highly correlated with the national index, but forecasts of the latter are more likely to be available.[4]

There is no database of headboat fees for the vessels operating in the GOM. Fee information was collected in industry surveys during 1987 and 1997 (Ditton *et al*. 2001),

[4] Also, regional income measures are not available on a monthly time-step. The correlations with the U.S. level for the 1986.1 – 2003.4 Quarterly Personal Income (SQ1) measures from the BEA for states within the GOM are as follows (www.bea.gov/regional/REMDchart): AL=0.9968, FL=0.9995, LA=0.9952, MS0.9971, TX=0.9983, and Gulfwide= 0.9997. After removing the trend, the correlations are still high at AL=0.9997, FL=0.8619, LA=0.4995, MS=0.7530, TX=0.9642, and Gulfwide=0.9781.

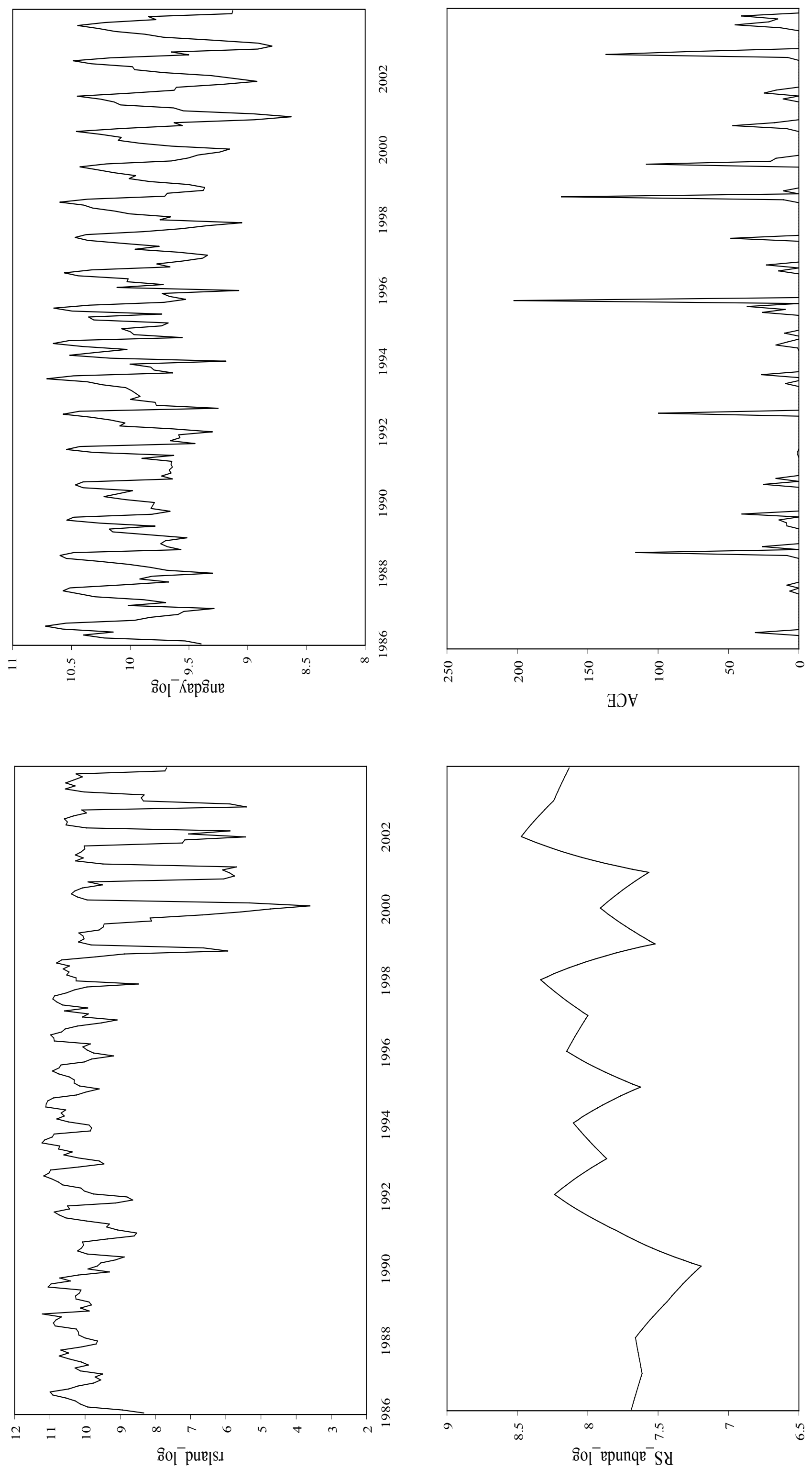

Figure 1. Monthly Time Series: 1986.01 – 2003.12 (continued)

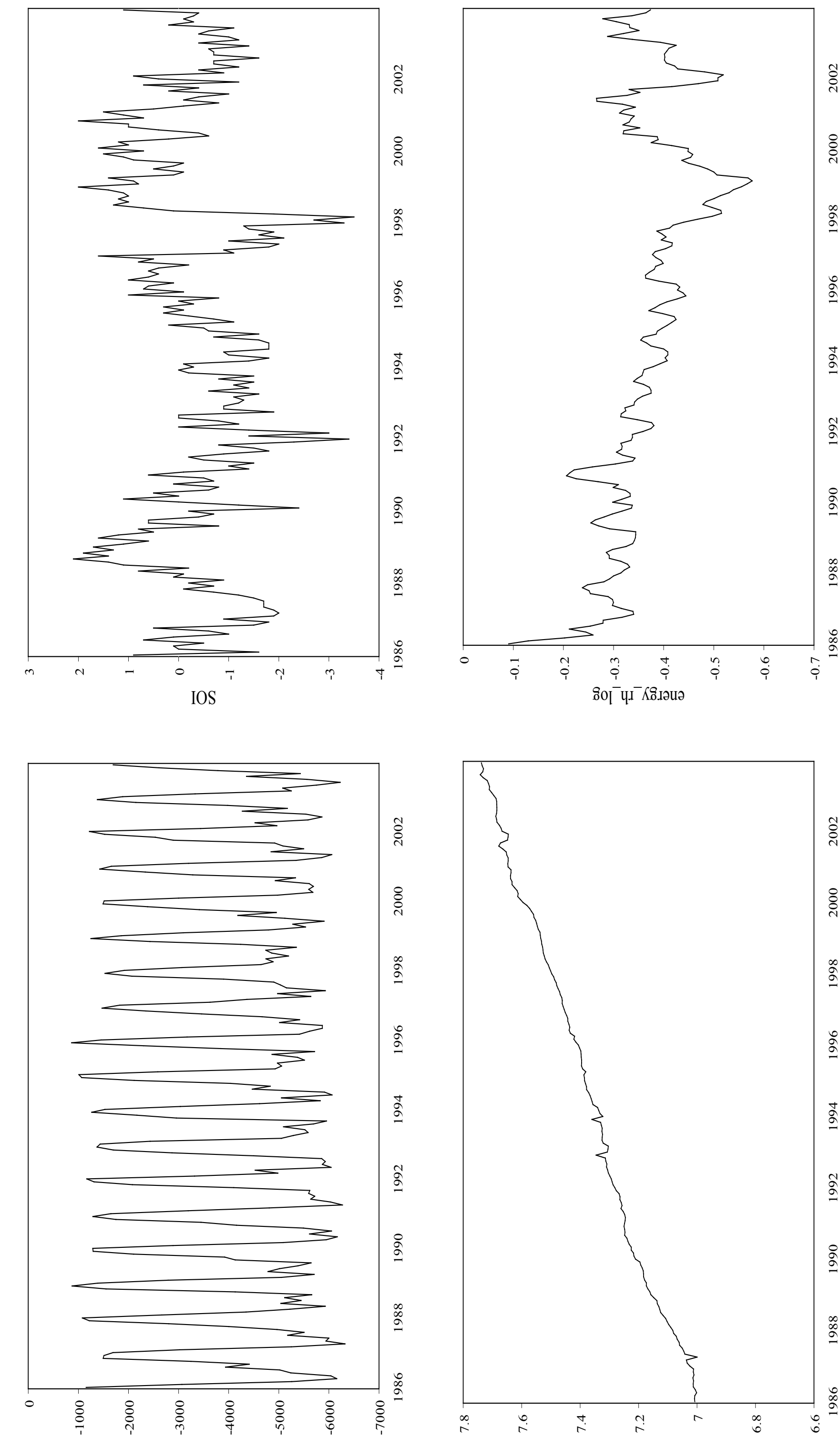

Figure 1. Monthly Time Series: 1986.01 – 2003.12 (concluded)

but this is not enough data to construct a monthly time series for our study period. Consequently, to proxy the price of a headboat trip we used the consumer price index (CPI) for energy from the Bureau of Labor Statistics. We recognize that this proxy for trip price is not optimal because changes in the cost of energy could affect the demand for angler days in a number of ways. First, higher energy prices decrease the income available to spend on other goods and activities, such as recreation. Second, energy price increases raise the cost of travel to headboat ports. Finally, the costs of headboat operations increase with higher energy prices, and operators tend to pass some of these costs on to customers via fuel surcharges (Ditton, Holland, and Gill 1992). These potential effects suggest a negative relationship between energy prices and headboat angler day demand. In the end, however, the net affect of energy prices on the demand for headboat services is an empirical question. This would also be the case for alternative headboat price proxies. The search for and examination of such alternatives is left for future research.

The energy CPI and the per capita income series were divided by the CPI for all items (less energy) before estimation to preserve homogeneity in the angler day demand equation (Alston, Chalfant, and Piggott 2002). All monthly values in the economic series are relative to the 1982-84 base year. The logarithms of the normalized energy price (*energy_rh_log*) and disposable income (*dpinc_rh_log*) series are shown in the bottom row of figure 1.

Climate Factors

Weather is defined and measured by variables such as temperature, cloudiness, precipitation, and radiation, and climate is the weather averaged over a time period of at least one month. We focus on climate indicators rather than individual weather variables. This approach is appropriate given the broad geographic area considered in this study and because predictions of climate indicators are more likely to be available for use in forecasting.

There are several connections between large-scale atmospheric-oceanic circulation and climate in the southeastern U.S.A. Among these are the El Niño-Southern Oscillation (ENSO), the Atlantic subtropical circulation or Bermuda High (*BH_NO*), the Pacific/North American Pattern, and the North Atlantic Oscillation. However, evidence appears strongest for ENSO and the *BH_NO* as separate sources of variation in the Southeastern climate (Katz, Parlange, and Tebaldi 2003). We also consider the effects of storm and hurricane activity with an index of cyclonic activity in the GOM.

ENSO is a variation between normal conditions and two extreme states associated with warm (El Niño) or cold (La Niña) sea surface temperatures in the eastern tropical Pacific (Trenberth 1997). In an El Niño winter, a strengthened jet stream moves farther south across the southern U.S.A., guiding winter storms into the GOM providing abundant rainfall and cooler temperatures. In La Niña winters, fronts and storms do not make it down to the GOM as often, and the winters are warmer and dryer than normal (Kiladis and Diaz 1989; Ropelewski and Halpert 1986). Note that the ENSO also affects hurricane activity during the late summer via changes in the Atlantic atmospheric circulation. For example, during El Niño events, increased vertical shear acts to limit the number of tropical disturbances that become hurricanes in the Atlantic basin (Bove *et al*. 1998).

We characterize ENSO in terms of the sea level air pressure differential between Tahiti and Darwin using the Southern Oscillation Index (*SOI*). The *SOI* is shown in the second graph (*SOI*) in the third row of figure 1. Note that dips in the *SOI* correspond with El Niño events, whereas peaks correspond to La Niña events. For example, the lowest dip in the *SOI* occurred in January 1998 and corresponds to the El Niño event that by some measures was the strongest of the century.[5] Therefore, relatively lower values of the *SOI*

[5] Warm events during the 1986-2003 study period occurred in 1986, 1987, 1991, 1997, and 2002; cold events occurred in 1988, 1998, 1999. These events refer to years defined on the ENSO cycle, October to September.

indicate wetter and cooler winter weather and fewer hurricane landfalls in the Southeast.

The *BH_NO* is a large-scale circulation system that has been associated with climate and weather in the southeastern U.S.A. Spring precipitation in the southeastern coastal states tends to be higher if the western edge of the *BH_NO* is east of its average position (Stahle and Cleveland 1992). Daily temperature levels and precipitation variability also tend to be higher when the BH_NO is east of its average position (Katz, Parlange, and Tebaldi 2003). The *BH_NO* index is shown in the first graph in the third row of figure 1. Higher values of the *BH_NO* index indicate locations farther east than normal. Thus, peaks in the *BH_NO* series tend to be associated with warmer and wetter conditions in the Southeast.

The National Oceanic and Atmospheric Administration's Accumulated Cyclone Energy (*ACE*) index is an appropriate measure for categorizing hurricane activity (Bell *et al*. 2000). The *ACE* index is the sum of the squares of the six-hourly maximum sustained wind speeds from all tropical cyclones that have winds of at least tropical storm strength. This measures the cumulative wind energy from tropical storms, hurricanes, and intense hurricanes occurring in a given area for a period of time. The monthly *ACE* index for the GOM from 1986 to 2003 is shown in the second graph (*ACE*) in the second row of figure 1. Highpoints in the *ACE* indicate increased hurricane and storm activity. For example, the peak during 1995 marks the most active hurricane season during the study period.

Initial Analysis of Data

The summary statistics and sources for the full sample (1986.01 to 2003.12) of the data are shown in table 2. Our initial analysis consists of tests for causality, stationarity, and cointegration for the headboat angler days and red snapper harvest series.[6] The results of the initial analysis will be used to specify a structural time series model.

Causality can be examined using a reduced form vector autoregression (VAR) for the logarithms of headboat angler days and red snapper harvest. We abstract, for now, from the exogenous variables and estimate a two variable VAR including an intercept, monthly dummies, and a trend. Based on the minimum value of the Akaike Information Criterion, the appropriate lag length in this headboat fishery VAR is twelve. Using procedures outlined in Lütkephol (2005, Sect. 3.6.1), the hypothesis that red snapper harvest does not Granger-cause angler days is rejected (*p-value*=.0008), whereas the hypothesis that angler days do not Granger-cause red snapper harvest cannot be rejected (*p-value*=.2627). Note that Granger-causality is evident when the lagged values of one variable or a group of variables help to predict another variable in the system. These results suggest that effort may respond to past harvest, but that past effort may not be useful in predicting current harvest. The hypothesis of no instantaneous causality is also rejected (*p-value*=.0026). There is instantaneous causality if knowing the value of one variable in the forecast period helps to improve the forecasts of the other variable. Note, however, that this concept is symmetric and the direction of the causality cannot be determined (Lütkephol and Kratzig 2004).

Accurate inference and forecasting with the headboat system requires that the endogenous variables be stationary. Specifically, headboat angler days and red snapper harvest should have a fixed (or trending) mean and variance over time. Otherwise, parameter distributions will be non-standard, and forecasts from the model will be inaccurate as variables in the system can become arbitrarily large or small (Hamilton 1994). Stationarity also has policy implications. Variables that are not stationary will tend to permanently absorb shocks and not return to a previous mean or trend. In fisheries analysis, the notion of stationarity could help determine whether policies will have permanent or transitory effects on the bioeconomic system.

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[6] All testing and estimation is performed using JMulTi (Lütkephol and Kratzig 2004) and verified with SAS on a Windows XP machine with a 3.46GHz*2 Pentium® D processor and 4.5GB of RAM.

Table 2
Summary Statistics: 1986.M1 - 2003.M12

Data	Model	Description	Mean	Min.	Max.	Std. Dev.
angday_log[1]	*Ln(D)*	Natural log of headboat angler days	9.90	8.63	10.72	0.43
rsland_log[1]	*Ln(H)*	Natural log of headboat red snapper harvest	9.74	3.61	11.23	1.38
rs_abunda_log[2]	*Ln(F)*	Natural log of red snapper abundance index (in thousands)	14.79	14.10	15.38	0.29
ACE[3]	**w**	Accumulated cyclonic energy index for the Gulf of Mexico	0.77	0.00	20.25	2.52
BH_NO[4]	**w**	Bermuda high index (in thousands)	–4.06	–6.32	–0.86	1.64
SOI[5]	**w**	Southern oscillation index for the ENSO	–0.33	–3.50	2.10	1.11
dpinc_rh_log[6]	*Ln(m)*	Natural log of normalized disposable personal income index	7.38	7.00	7.74	0.21
energy_rh_log[7]	*Ln(c)*	Natural log of normalized energy price index	–0.36	–0.58	–0.09	0.08

[1] Estimates of aggregate effort and harvest are from the NMFS Headboat Survey in the GOM.
[2] Estimated biomass in the GOM red snapper stock assessment (NMFS 2005).
[3] The ACE index for the GOM was computed by Hugh Willoughby using the maximum sustained wind speed data from North Atlantic hurricane database at the U.S. National Hurricane Center (Neumann *et al*. 1999).
[4] The position of the *BH_NO* is measured as the difference between the gridded monthly sea level pressure (SLP) near New Orleans (30° N, 90° W) and Bermuda (32.5° N, 65° W). The SLP data were accessed on 1 May 2008 from www.cgd.ucar.edu/cas/catalog/nmc/rean/press/means.html
[5] The SOI was accessed on 1 May 2008 from www.cpc.ncep.noaa.gov/data/indices/soi
[6] The monthly U.S. disposable income per capita series (A229RC0) was taken from T*able 2.6. Personal Income and Its Disposition, Monthly* in the National Economic Accounts accessed on 1 May 2008 from bea.gov/bea/dn/nipaweb/SelectTable.asp. This series was normalized by the monthly All Urban Consumers U.S. city average Consumer Price Index (CPI) for all items less energy series (CUUR0000SA0LE) accessed on 1 May 2008 from www.bls.gov/cpi/home.htm
[7] The monthly U.S. city average energy CPI for All Urban Consumers (CUUR0000SA0E) was accessed on 1 May 2008 from www.bls.gov/cpi/home.htm. This series was normalized by the monthly All Urban Consumers U.S. city average Consumer Price Index for all items less energy series (CUUR0000SA0LE) was accessed on 1 May 2008 from www.bls.gov/cpi/home.htm

Examination of the headboat angler days and red snapper harvest series in figure 1 suggests a level shift around 1998 when the red snapper season length changed substantially. Standard Augmented Dickey-Fuller (ADF) tests for stationarity can have very low power if level shifts are ignored (Perron 1989). Therefore, following Lanne, Lütkephol, and Saikkonen (2002) we use a version of the ADF that allows for a level shift in the mean. Specifically, a shift dummy is subtracted from the logarithmic series for angler days and harvest before performing the ADF tests. The shift dummy equals one beginning in December of 1997 and zero in prior periods.

The results of the level shift unit root tests for the logged headboat angler day and red snapper harvest data series (and differenced series) are shown in table 3.[7] Lag lengths for all univariate tests were selected by testing down to the highest significant lag in a series of ADF test regressions without the level shift (Ng and Perron 1995). A constant term and monthly dummies were also included in the test regressions to control for seasonality. In addition, the test regression for angler days includes a trend to address the slight downward slope in the mean of this series. Comparing the test statistics with the 5% critical

[7] Results for ADF tests that omit the level shift adjustment are available upon request. These tests provide even less support for the rejection of the unit root hypothesis.

values indicates that unit root hypothesis of no stationarity cannot be rejected in the angler day and red snapper harvest series. However, the hypothesis of unit roots is rejected in the differenced series, suggesting that headboat angler days and red snapper harvest are each integrated of order one.

As angler days and red snapper harvest series are each integrated series, shocks to these fishery variables can have permanent effects. It is possible, however, that a linear combination of effort and harvest is stationary. In this case, there is a long-run equilibrium relationship in the system indicating that effort and harvest are cointegrated (Engle and Granger 1987). Cointegration between headboat effort and red snapper harvest in the GOM is a plausible hypothesis given the heavy dependence of headboats on this species.

We use a rank order test proposed by Saikkonen and Lütkephol (2000) to evaluate cointegration between headboat angler days and red snapper harvest in the presence of a level shift. Briefly, standard Johansen (1994) rank order tests for cointegration are performed on the angler day and red snapper harvest series after removing the deterministic terms, including the level shift. Test equations include a constant, seasonal dummies, and a trend that is restricted to the cointegration relationship. The lag length for the cointegration test is the length selected above for the VAR system (Lütkephol 2005). The results of the tests are shown in table 3, where the test statistics indicate a rejection of the rank order zero (*r=0*) and the inability to reject the order of one (*r=1*), both at the 95% level. These results suggest that the series are cointegrated of order one and can be modeled in vector error correction form.

Table 3
Unit Root and Cointegration Tests

Data	Deterministic Terms	No. of Lagged Differences		Test Statistic	5% Critical Value
--Unit Root Tests--					
angday_log	constant, seasonal, shift, and trend	11		–1.92	3.03
rsland_log	constant, seasonal, and shift	12		–2.38	–2.88
Δangday_log	constant, seasonal, and shift	10		–6.71	–2.88
Δrsland_log	constant, seasonal, and shift	1		–3.16	–2.88
--Cointegration Tests--					
angday_log and rsland_log	constant, seasonal, shift, and trend	11	H_0: *r=0*	23.61	15.76
			H_0: *r=1*	5.10	6.79

Sample period: 1986.M1-2003.M12. Critical values for the level shift (1997.12) unit root and cointegration tests are from Lane, Lütkephol, and Saikkonen (2002) and Johansen (1995), respectively.

Specification of the Structural Vector Error Correction Model

The initial analysis finds that the headboat effort and red snapper harvest are integrated series, suggesting that first differencing is necessary before estimation. However, this would result in a loss of information about the long-run relationship between these series. The additional finding that the harvest and effort series are actually cointegrated implies information about the long-run relationship that can be extracted if the sportfishing VAR in equation (5) can be reformulated as the following SVEC model (Breitung, Gruggemann, and Lütkephol 2004):

$$\Gamma \Delta \mathbf{y}_t = \alpha \left(\left[1 \quad \beta \right] \mathbf{y}_{t-1} + \mu + \delta\, t_{t-1} \right) + \sum_{i=1}^{11} \boldsymbol{B}_i \Delta \mathbf{y}_{t-i} + \mathbf{G}\mathbf{x}_t + \boldsymbol{\eta}\, \mathbf{S}_t + \boldsymbol{\varepsilon}_t, \tag{6}$$

where Δ is the first difference operator, $\alpha[1\ \beta] = -(I_2 - \boldsymbol{A}_1 - \cdots - \boldsymbol{A}_{12})$, $\boldsymbol{B}_i = -(\boldsymbol{A}_{i+1} + \cdots + \boldsymbol{A}_{12})$, $Ln(m_t)$ = *dpinc_rh_log*, $Ln(c_t)$ = *energy_rh_log*, and the vectors of exogenous regulations and climate variables in $\mathbf{x}_t$ are specified as $\mathbf{r}_t$ = (*rs_closer rs_bagr rs_msr*) and $\mathbf{w}_t$ = (*ACE BH_NO SOI*), respectively. Also, the SVEC formulation splits the deterministic vector, γ, from equation (5) into a constant, μ; monthly dummies, $\mathbf{S}_t$; and a trend, t_{t-1}, with the trend restricted to the cointegration relationship. The parameters β and $\alpha = (\alpha_1\ \alpha_2)$ specify the long-run portion of the model, with the former containing the cointegrating relations and the latter representing the loading coefficients. Essentially, β measures the long-run cointegrating relationship between harvest and angler days, and α measures how the system changes in response to deviations from the long-run equilibrium (Engle and Granger 1987). The red snapper harvest cointegrating parameter has been normalized to unity so that the effort parameter, β, in this vector measures how red snapper harvest changes when angler days change in equilibrium.

Several parameter restrictions are applied to the SVEC model based on the VAR model of for-hire sportfishing shown in equation (5) and the initial analysis of the data. First, the matrix of contemporaneous effects, Γ, is restricted to be upper triangular with ones on the diagonal. This formulation is consistent with our sportfishing model where the current value of angler days enters the red snapper harvest equation. Second, based on the Granger causality tests, we restrict the parameters, B_i, on the eleven lags of logged angler days (differences) in the red snapper harvest equation to zero. One level lag still appears in the cointegration relationship to measure changes in the system when logged red snapper harvest and angler days deviate from their long-run average relationship. These restrictions are also consistent with the for-hire sportfishing model, whereby expected harvest appears in the angler day demand equation. Finally, the for-hire sportfishing model suggests restricting the parameter to be zero for the red snapper biomass index in the angler day equation and the parameters equal zero on the energy price and income indices in the red snapper harvest equation.

A two-stage estimation procedure is used to obtain estimates of the system parameters (Lütkephol and Kratzig 2004). First, estimates of parameters in the cointegrating equation obtained via OLS using the red snapper harvest equation in (6). Note that in estimating this version of the red snapper harvest equation, the cointegration terms $\alpha([1\ \beta]\mathbf{y}_{t-1} + \mu + \delta_{t-1})$ are entered in reduced form as $\pi_1 + y_{1,t-1} + \pi_2 y_{2,t-1} + \mu' + \delta' t_t$, and the current first difference of angler days is included to reflect the structural form. Normalized estimates of $\hat{\beta}$, $\hat{\mu}$, and, $\hat{\delta}$ can then be recovered as:

$$\hat{\pi}_2 / \hat{\pi}_1, \mu' / \hat{\pi}_1, \text{ and } \delta' / \hat{\pi}_1,$$

respectively. In the second step,

$$\left[1 \quad \hat{\beta} \right] \mathbf{y}_{t-1} + \hat{\mu} + \hat{\delta} t_{t-1}$$

is used in place of $[1\ \beta]\mathbf{y}_{t-1} + \mu + \delta t_{t-1}$, and the remaining parameters of system are estimated by *3SLS*.[8] For comparison, we also present *3SLS* estimates of the parameters of

[8] Estimating the system via full information maximum likelihood produced nearly identical results as did equation-by-equation OLS. The latter result suggests that the system is recursive; *i.e.*, angler day demand is determined first and then entered into the red snapper harvest equation (Green 2000). We present the 3SLS results because they address the potential for contemporaneous correlation and do not rely on the multivariate normality of the errors.

the naïve version of system (5) that includes seasonal dummy and trend variables, but leaves out the autoregressive terms (*i.e.*, $\alpha_{i,11} = \alpha_{i,21} = 0$) and the one lag of angler days in the harvest equation implied by cointegration. Recall that the lags of red snapper harvest remain in the angler day equation of the naïve model to proxy harvest expectations as specified in system (5). The difference between the SVEC and the naïve models amounts to a total of 25 restrictions: 12 in the angler day demand equation and 13 in the red snapper harvest equation. Again, this comparison model is meant to represent an approach that does not formally consider the time series properties of the data.

Results

Model Diagnostics and Estimates

Analysis of the SVEC model residuals and diagnostics indicates a reasonably good fit to the data generating process.[9] A Breusch-Godfrey test of no residual autocorrelation at five lags is rejected ($\chi^2(20) = 52.99$), but visual inspection of the residuals demonstrates little, if any, auto or cross correlation outside of the 95% confidence interval bounds for either series. Tests for joint nonnormality of the residual series cannot be rejected ($\chi^2(4) = 231.85$) (Doornik and Hansen 2008). The nonnormality can be attributed to excess kurtosis (leptokurtosis) in the red snapper harvest equation residuals. The joint hypothesis of no excess skewness is rejected ($\chi^2(2) = 5.47$), but the joint hypothesis of no excess kurtosis is not rejected ($\chi^2(2) = 226.37$). Furthermore, Jarque-Berra univariate tests reject normality in the red snapper harvest residuals (χ^2 (2) = 228.57), but fail to reject normality in the angler day residuals (χ^2 (2) = 1.37). The measured kurtosis of the red snapper harvest residuals is 8.13. However, density plots (not shown) of the residual series suggest that this is not a severe problem and that the residuals are approximately normally distributed. A related issue is the inability to reject ($\chi^2(45) = 88.94$) the hypothesis of multivariate autoregressive conditional heteroskedasticity (ARCH) at five lags (Doornik and Hendry 2006).[10] Again, this problem can be traced to ARCH in the red snapper harvest equations residuals. A univariate hypothesis test of no ARCH with 16 lags is not rejected for the angler day residuals (χ^2 (16) = 22.62), but is rejected for the red snapper harvest residuals (χ^2 (16) = 54.52). These results suggest that the SVEC model will, in general, forecast angler days better than red snapper harvest. Red snapper harvest estimates and forecasts could be improved with adjustments for ARCH. This is left for future research.

Collectively, the 25 zero-restrictions implied by the naïve model can be rejected (p=0.001), indicating that the SVEC model fits the data better than the naïve specification. The source of the SVEC advantage is revealed upon examination of the zero-restrictions implied by the naïve model in each equation. The zero-restrictions on the autocorrelation terms and the one lag of angler days implied by cointegration in the harvest equation are rejected (p=0.002), while the autocorrelation restrictions in the angler day equation are not rejected (p=0.566). These results emphasize the empirical importance of accounting for autocorrelation and cointegration, at least in the red snapper harvest equation.

Parameter estimates for the key SVEC and naïve model variables are shown in table 4.[11] The parameters on the policy variables in the harvest equation (*rsland_log*) are very similar between the two specifications, but those on angler days (*angday_log*) and red snapper biomass (*RS_abund_log*) are noticeably different. The latter might be due to the failure of the naïve specification to address the cointegration between harvest and effort.

[9] The full set of model diagnostics, including all residual plots, is available on request.

[10] The multivariate ARCH test employed runs out of degrees of freedom when testing over a large number of lags. Therefore, we chose to test at five lags even thought the model was estimated with twelve lags.

[11] The parameter estimates for the lagged endogenous variables and the results for the tests of the individual parameter restrictions are available on request.

The effect of the one significant policy variable (*rs_closer*) in the angler day model is less in the naïve specification as is the effect of the ENSO (*SOI*). This suggests that the naïve model will underestimate the effects of closed seasons and changes in climate patterns on effort. Finally, note that the standard errors of the parameters in the both equations are larger in the naïve specification. In what follows, we focus on the parameter estimates from the SVEC specification. We return to the comparison of the specifications in the discussion of forecasting capabilities.

Table 4
Parameter Estimates

Data Variable	rsland_log		angday_log	
	SVECM	Naïve	SVECM	Naïve
rs_closer	–4.616** (0.821)	–4.899** (1.525)	–0.761** (0.385)	–0.391 (0.439)
rs_blr	0.006** (0.001)	0.006** (0.002)	0.001 (0.000)	0.001 (0.001)
rs_msr	–0.148** (0.051)	–0.164* (0.093)	–0.034 (0.024)	–0.012 (0.028)
ACE	–0.002 (0.002)	–0.002 (0.002)	0.000 (0.001)	0.000 (0.001)
BH_NO	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
SOI	–0.036 (0.039)	–0.05 (0.049)	–0.023* (0.012)	–0.005 (0.013)
dpinc_rh_log			0.057 (0.046)	1.267 (0.97)
energy_rh_log			–0.139 (0.246)	0.043 (0.239)
angday_log	0.582** (0.246)	1.826** (0.499)		
RS_abunda_log	0.297** (0.1)	0.525** (0.236)		
α	–0.517** (0.057)		–0.054** (0.021)	

Sample period: 1987.M1-2003.M12.
Standard error shown in parentheses below the estimate.
* Significant at the 0.10 level; ** Significant at the 0.05 level.

The first stage of the SVEC model estimation yielded the OLS estimates of $\hat{\pi}_1 = -0.555$, $\hat{\pi}_2 = 0.443$, $\mu' = -0.474$, and $\delta' = 0.008$ that were used to generate the following normalized estimates of the cointegration parameters: $\hat{\beta} = -0.799$, $\hat{\mu} = 0.854$, and $\hat{\delta} = -0.015$. The standard error of the cointegrating parameters is not calculated because the *superconsistency* of this estimator ensures a small variance in relatively large samples (Stock 1987). The value of the cointegrating parameter (0.7990) indicates that in long-run equilibrium, red snapper harvest is inelastic with respect to changes in angler days.

Estimates on the logged exogenous variables can be interpreted as constant short-run elasticities for small changes. For the climate variables, the short-run percentage change in angler days or red snapper harvest due to a percent change is calculated as the value of the exogenous variable times the corresponding parameter. Semi-elasticities can also be calculated for these variables by multiplying the relevant coefficient by 100. Elasticities for the regulatory variables are more complicated because the bag and size limit values are interacted with the closed season variable. For each equation, the closed season, bag limit, and size limit elasticities are calculated as $r_{i1}\,(g_{i1} - g_{i2}\,r_{i2} - g_{i2}\,r_{i2})$, $g_{i2}\,r_{i2}\,(1 - r_{i1})$, and $g_{i3}\,r_{i3}\,(1 - r_{i1})$, respectively.

The parameter on angler days (*angday_log*) shown in the red snapper harvest equation shown in table 4 is significant and positive, suggesting that a 1% increase in headboat angler days leads to 0.582% increase in harvest. Similarly, a 1% increase in red snapper abundance contributes to a 0.297% increase in red snapper harvest. These results suggest that red snapper harvest response to changes in angler days and abundance is inelastic in the short run. As noted above, red snapper harvest is slightly more responsive (0.799) to changes in angler days when the system is at the long-run equilibrium. According to the adjustment parameters (α), corrections for deviations from the long-run equilibrium occur via changes in red snapper harvest at a rate of -0.517 and changes in angler days at a rate of -0.054. The signs on the adjustment parameters are correct in that angler days, and therefore harvest, adjust downward when the harvest is above equilibrium. Furthermore, both of the adjustment parameters are statistically significant, lending support to the system estimation approach.

Regulations on the recreational harvest of red snapper have the expected effects in this fishery. With 50% of the month closed to red snapper fishing (*rs_closer*), closing an additional percent of the month contributes to a 1.36% and 0.145% reduction in red snapper harvest and angler days, respectively. Bag limit (*rs_blr*) changes have a positive effect on the system, whereby a 1% change in the bag limit (from four fish) during the open season contributes to a 0.024% change in red snapper harvest. Changes in the minimum size limit (*rs_msr*) have a negative effect on the system, such that a 1% change in the size limit (from sixteen inches) results in a -2.368% change in red snapper harvest. The direct effects of bag and size limit changes on angler days are not significantly different from zero. These policies may affect angler days indirectly as responses to changes induced in red snapper harvest. However, as noted above, the angler day response to changes in red snapper harvest is likely to be relatively small.

The only significant climate phenomenon was the ENSO (*SOI*), and this factor appears to enter the system via the angler day demand equation. Specifically, a one unit increase in the *SOI* leads to a 2.3% decrease in angler days. This finding implies that cooler, wetter winter weather in the Southeast during El Niño periods increases headboat fishing effort and, subsequently, the harvest of red snapper. Perhaps headboat anglers, when blessed with nice winter weather, hunt or play golf instead of going fishing (Ditton and Sutton 2004). This finding could also reflect the decrease in intense landfalling hurricanes associated with El Niño years.

Log relative personal disposable income (*dpinc_rh_log*) and energy prices (*energy_rh_log*) are not significant in either the SVEC or the naïve specification. This lack of significant influence could reflect actual conditions or be due to an inappropriate choice of index for income and the cost of headboat trips. Note, however, that the average values of the income and energy price parameters have the expected signs.

Forecast Accuracy and Policy Example

As a simple test of the SVEC model's forecasting ability, consider the forecasted and observed values of the system variables for the two years following the estimation sample period. Conditional forecasts can be simulated using the SVAR representation of the system with the estimated parameters (Lütkephol 2005). Given historic (before time T) values of the endogenous variables and forecasted values (after time T) of the exogenous variables and assuming ε_t is independent white noise, an h-step ahead forecast at time T is:

$$\hat{\mathbf{y}}_{T+h|T} = \Gamma^{-1}\left(\sum_{i=1}^{12}\hat{A}_i\hat{\mathbf{y}}_{T+h-i|T} + \hat{\mathbf{G}}\mathbf{x}_{T+h} + \hat{\eta}\mathbf{S}_{T+h} + \hat{\nu} + \hat{\phi}t_{T+h-1}\right), \tag{7}$$

where $\hat{\mathbf{y}}_{T+h|T} = \mathbf{y}_{T+j}$ for $j \leq 0$, $\hat{\nu}=\hat{\mu}\cdot\hat{\alpha}$, $\hat{\phi}=\hat{\delta}\cdot\hat{\alpha}$ and the estimated A matrices are related to the estimated B matrices as shown below equation (6). Forecasts using the naïve model can be calculated in a similar way.

Three measures of the 2004-2005 forecast accuracy are shown in table 5 for the SVEC and naïve models. The first measure of forecast accuracy is the root mean square forecast error, and the second two measures are versions of the Theil's U inequality coefficient (Green 2000). For Theil's U coefficients, a value of one indicates a forecast that is no better than assuming that the next month will be like the current month. The version of Theil's U in levels measures the accuracy of the forecast on average, whereas the version in differences measures the ability of the forecast to track turning points in the data. By all measures, the SVEC model forecasts angler days better than the naïve model. According to the Theil's U in differences, the main advantage of the SVEC model over the naïve model is its ability to forecast changes in the angler day series. The forecast measures do not differ much, however, between the SVEC and naïve models in forecasting red snapper harvest.

Table 5

Forecast Accuracy Measures: 2004-2005

	angday_log		rsland_log	
Measure	SVEC	Naïve	SVEC	Naïve
Root Mean Square Error	0.16	0.28	1.61	1.63
Theil's U in Levels	0.02	0.03	0.19	0.19
Theil's U in Differences	0.43	0.73	0.78	0.79

Theil's U in levels tracks the ability to forecast the mean, whereas Theil's U in differences measures the ability of the forecast to track turning points in the data.

At first glance, the accuracy of the SVEC model forecasts, especially for the angler day equation, may seem surprising given the general lack of structural parameter significance shown in table 4. Recalling the seasonality evident in the angler day series plot in figure 1, suggests that a substantial portion of this accuracy is afforded via the monthly dummy variables. Though not necessarily correct given the results of the unit root and cointegration tests, we can compare R^2 measures from OLS regressions to get an idea of the relative contribution of the dummy variables in the angler day model. An OLS regression of the 11 monthly dummy variables and a constant on the levels of the log angler day series has an adjusted R^2 of 0.70. Adding the remaining variables in the naïve specification raises the adjusted R^2 to 0.83; however, adding the autoregressive terms to approximate the reduced form of the SVEC specification does not result in further improvement in the adjusted R^2. The latter finding is consistent with the inability to reject the autocorrelation restrictions in the SVEC angler day equation reported in the previous section.

Figure 2 shows the actual headboat angler days and red snapper harvest for 2004.1 to 2005.12 and the corresponding SVEC model forecasts using the actual values for the exogenous variables and the angler days and red snapper harvest from 2003.01 to 2003.12 as starting values. The logarithmic and level forecasts are shown in the upper and lower panels, respectively. The naïve model forecasts are not shown in the interest of space.

Note that the level forecasts are based on the exponential operator. Arino and Franses (2000) have shown that simply taking exponentials of forecasts for logged data can lead to biased level forecasts, especially for long time horizons. However, this bias does not appear severe in our relatively short SVEC model forecasts. The 95% confidence intervals shown are calculated assuming normally distributed disturbances and the standard deviation of the forecast error (Lütkephol 2005).

The logarithmic and level angler day forecasts in figure 2 track the actual values extremely well, but the red snapper harvest forecasts overestimate the actual values during the peak summer season. The inaccuracies in magnitude of the red snapper harvest forecasts were anticipated in the model diagnostics where we found evidence of ARCH and leptokurtosis in the residuals for this series. However, the SVEC model appears to forecast changes in the red snapper well and, if necessary, the model can be calibrated to adjust the overestimated level forecasts during the summer periods.

The SVEC model of the headboat fishery can be used to forecast effort and harvest under different policy scenarios. For example, the SVEC model was recently used in an analysis of the rebuilding plan options for the red snapper fishery in the GOM.[12] We simulated the counterfactual effect of each policy alternative as if it had been implemented at the start of 2004.[13] The difference between the actual and forecasted levels for 2004 shown in figure 2 was used to calibrate the policy forecasts. Each policy alternative is a combination of changes in the red snapper season, bag limit, and minimum size limit. All other model variables are assumed to be at the 2004 values. Note that impulse response analyses could be used to explore the effects of each type of policy in isolation. However, we prefer to emphasize the strength of the SVEC model in measuring the effects of complex, real-world management schemes.

Figure 3 shows the potential outcomes of three policy alternatives. Note that the labels of the three policies (2, 8, and 9) correspond with the actual numbers of the GOM red snapper rebuilding plan options in the recent analysis. The first policy (2) maintains the four-fish bag limit and the sixteen-inch minimum size limit, but shortens the open season to run from May 15 to September 30, instead of April 21 to October 31. The effects of the shortened season are most noticeable as a rightward shift and compression of the red snapper harvest series. The angler day series is also shifted slightly by the policy. A second policy (8) lowers the bag limit from four to two fish, lowers the minimum size limit from sixteen to fifteen inches, and shortens the open season to run from May 15 to October 15. Note that the red snapper harvest series shifts due to the shorter season, but that harvest actually increases in the open season due to the lower minimum size limit. Angler days are also higher in the open season for this policy alternative. The third policy (9) also considers a two-fish bag limit, but the minimum size limit is lowered further to thirteen inches, and the season is shortened even more to go from May 15 to September 15. This policy alternative results in a much more compressed distribution of red snapper harvest across the year, with an almost doubling of harvest in the peak open season. The level of angler days is also noticeably higher during the summer peak.

Summary and Conclusions

Analyses of fisheries rebuilding plans require forecasts of harvest, effort, and changes in economic welfare. Forecasts require an understanding of the time series properties of fishery data and the ability to control for influences outside the fishery. There is little published research on the behavior of recreational fisheries over time and how this infor-

[12] Information about the relevant environmental impact statement (EIS) is available at http://sero.nmfs.noaa.gov/sf/RedSnapper/RedSnapperDocs.htm

[13] The analysis for the EIS actually considered the effects on angler days and harvest in 2003. We use 2004 here to be comparable with the forecast simulations.

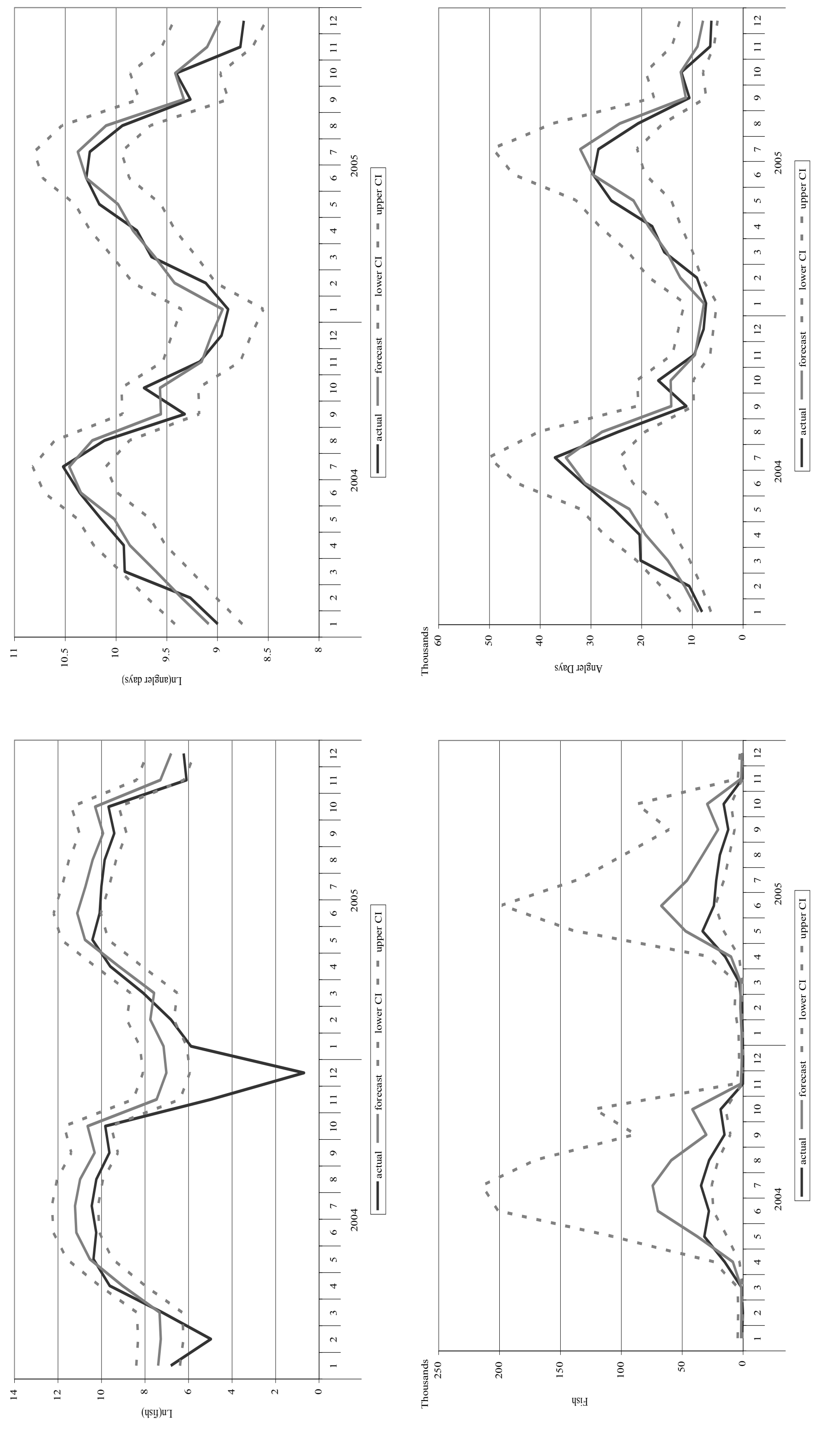

Figure 2. Forecasted versus Actual Fishery Series in Logarithms (Upper) and Levels (Lower): 2004-2005

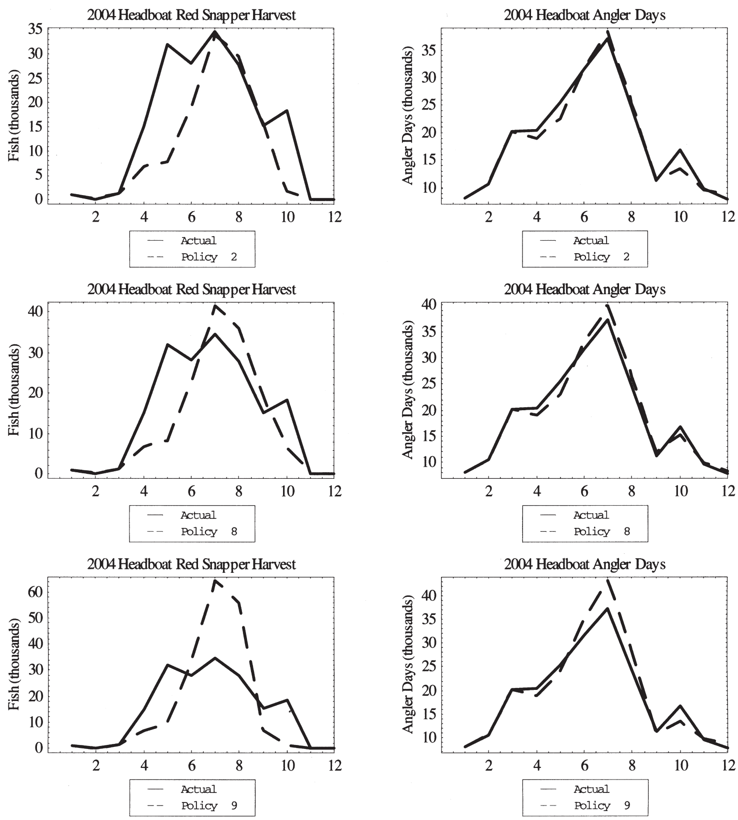

Figure 3. Red Snapper Regulatory Amendment Case Study

mation can be used to evaluate fishing regulation changes. We developed and estimated an econometric model of for-hire sportfishing that can be used to forecast the effects of policy changes in the presence of climate and economic variations.

The econometric model of for-hire sportfishing was initially developed as a structural VAR with equations for angler demand and harvest as a function of regulatory, climate, and economic variables. The model was specified based on monthly aggregate data from the GOM headboat fishery for red snapper. An initial analysis of the data indicated that effort and harvest are cointegrated series in this fishery and that past red snapper harvest predicts headboat effort, but not conversely. The former result suggests that unexpected events can have permanent effects on average effort and red snapper harvest without changing the long-run relationship between these variables. The latter result implies that headboat angler days appear to respond to past changes in red snapper harvest. These results were used to justify additional restrictions and a reformulation of the SVAR model as an SVEC model.

The final SVEC specification also included measures of red snapper biomass, regulations, climate activity, and economic factors. The index for adult red snapper biomass had a significant influence on red snapper harvest, as did contemporaneous values of headboat angler days. Changes in the red snapper season length directly affect both red snapper harvest and angler days. However, bag and minimum size limits only directly affect red snapper harvest.

National measures of disposable income and energy prices were used to proxy the anglers' incomes and their cost for a headboat trip. The parameters on these factors had the expected sign in the angler days equation, but neither was statistically significant. The lack of a statistically meaningful influence could reflect actual conditions or be due to an inappropriate choice of indices. These coarse factors for income and headboat prices were used because finer proxies were not available for the study area, and projections of these aggregate series are typically available for use in longer-term forecasts.

We considered climate indices for the effects of tropical cyclone activity, the Bermuda High, and the ENSO. However, only the index for the ENSO was a statistically significant influence on the fishery system. The ENSO was negatively correlated with angler days such that, for example, El Niño type events increase headboat effort. This result was unexpected, but it does not preclude ENSO forecasts for the southeastern U.S.A. from being used in predictive models of sportfishing effort and harvest.

The SVEC model forecasts well out of sample, especially for the headboat effort series. A comparative strength of the SVEC model, relative to a more naïve specification that omits autocorrelation and cointegration terms, is the ability to accurately forecast changes in headboat angler days. Additional forecast simulations were conducted to demonstrate the use of the model in policy analysis.

The results reported in this article demonstrate how to address the time series properties of effort and harvest and influences outside the fishery when forecasting policy outcomes. It turns out that the more sophisticated SVEC modeling results for our case study are not all that different from a more naïve structural specification that ignores autocorrelation and cointegration. Further work is necessary to verify if these results and the relationships uncovered for the GOM red snapper headboat fishery hold for other fisheries and modes of fishing. Specifically, there is a need to test for effort and harvest stationarity and cointegration in other areas and sportfishing modes. Future analyses should also attempt to incorporate additional influences on the recreational fishery system, including commercial fishing activity and harvest for related species. Consideration of other indices for economic factors would also be useful. The SVEC model developed in this article can be used to forecast the effects of fishery management. For example, skillful forecasts of ENSO appear six months in advance and could be used in fishery management forecasts. Whether such climate predictions would add to or subtract from the uncertainty surrounding the effects of management is another question for future research.

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