A TIME-SERIES ANALYSIS OF U.S. IMPORT PRICES AND ALASKA PROCESSORS' WHOLESALE PRICES FOR KING CRAB

A report by the Alaska Fisheries Science Center for
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Abstract

This report describes results of applying a dynamic econometric model that is widely used in macroeconomics and finance to time series of domestic and foreign sales price indices which are relevant to Alaska's king crab fishery. A bivariate vector autoregression (VAR) was performed with time series from Alaska's Commercial Operators Annual Report (COAR), over the period 1991-2006, and time series from the U.S. Merchandise Trade Statistics on king crab imports over the same period. Estimation and testing procedures that are widely used in financial econometrics were used here to select a model of king crab prices such that critical assumptions were not rejected. After model selection, 2 hypotheses were tested using these data: One hypothesis is that rationalization of the Bering Sea and Aleutian Islands crab fisheries in fall 2005 had a detectable statistical effect on the price series for king crab from the COAR or U.S. trade statistics. The other hypothesis is that certain dynamic relationships are present in the model which implies one set of variables is helpful in forecasting another set. There are 2 versions of this second hypothesis: One is that U.S. import prices for king crab are useful in forecasting future values of the COAR price index for wholesale prices, and the opposite implication is that price statistics from the COAR help forecast import prices of king crab. Tests of these hypotheses did not produce any significant results. Therefore, conclusions in the report are that i) rationalization was not a significant factor through 2006 in prices received by U.S. producers for Alaskan king crab, and ii) COAR prices over the period 1991-2006 can be treated as statistically separate, in a time series sense, from U.S. prices for imports of king crab.

1. Introduction

In October 2007, a market report in National Fisherman magazine was titled "Flood of Russian kings negates price gains expected with rationalization." This title suggests 2 distinct, and interesting, hypotheses about recent U.S. price dynamics for king crab: First, prices of U.S. imports, primarily from Russia, may be statistically related to prices received for king crab by U.S. producers. Economic theory would suggest that the price of imports is important if U.S. and Russian products compete in domestic markets to a significant degree. The second hypothesis is that rationalization led to a structural break in prices of Alaska king crab. In particular, rationalization was expected to have a positive effect on prices but this effect may have been swamped by the negative effect (under the first hypothesis) on prices implied by the recent influx of Russian king crab in U.S. imports. The time series analysis described in this report investigates both hypotheses. In particular it tests for the presence of a structural break after rationalization, and whether there has been a significant dynamic relationship between wholesale prices received by Alaska processors and prices paid for U.S. imports of king crab.

Time series methods used in this report are based on the stationary vector autoregression (VAR) model (e.g. Ch. 11 in Hamilton 1994). This type of model can be interpreted as a reduced-form and a-theoretical description of a dynamical system. Within this statistical framework, alternative models that represent different restrictions implied by economic theory can be tested. This type of model was popularized in macroeconomics by, for example, Sims (1980), and VAR models are now widely used in the analysis of financial time series (Zivot and Wang 2003). These models have also been selectively applied in fisheries economics (e.g. Rosenman 1987, Dalton 2001). Zivot and Wang (Ch. 11) state that the VAR model is "one of the most successful, flexible, and easy to use models for the analysis of multivariate time series" and has "proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting." These authors note that forecasts from a VAR model are often superior to forecasts from univariate time series models, or theory-based simultaneous equations models. Procedures used for estimation and testing of the VAR model in this report are described fully in Ch. 11 of Zivot and Wang (2003). Consequently, statistical tables and graphics in the report were produced from routines in S+, and in particular, the S+Finmetrics module. To economize, only a brief introduction to the model, methods of estimation, and testing are given here. Interested readers are referred to the list of references at the end of this report for a more comprehensive treatment of VAR models.

The rest of the report is organized as follows. Sec. 2 introduces the VAR model and describes methods used for estimation, testing, and forecasting. Sec. 3 documents the construction of time series that are used with the model from Alaska's Commercial Operators Annual Report (COAR) on average wholesale prices received by U.S. processors for Alaskan king crab, and from the U.S. Census Bureau's Merchandise Trade Statistics on the average price paid for U.S. imports. Sec. 4 presents the results of model estimation, diagnostic tests that form the basis of model selection, price forecasts from the selected model, and statistics that are used to test the pair of hypotheses about U.S. prices for king crab identified above. Sec. 5 summarizes the main conclusions in the report. An appendix at the end presents several results on forecasting U.S. import and wholesale prices with VAR models.

2. Model, Estimation, and Testing

The simplest VAR model can be represented by a pair of first-order difference equations that describe, in appearance, a simple dynamical system but in fact it can display very complicated behavior. In matrix notation, x_t is a vector of variables in time t, c is a vector of constants (i.e. intercepts), A is a square matrix that is invertible which satisfies certain bounds on its eigenvalues (in particular, these are real numbers and each diagonal element of A is strictly less than 1 in absolute value), and ε_t is an uncorrelated multivariate normal random process with a mean value of zero. The process for x_t satisfies the first-order matrix difference equation:

$$x_t = c + Ax_{t-1} + \varepsilon_t. \qquad (1)$$

These assumptions imply that the process for x_t is (strictly) stationary (e.g. see Fuller 1976). A more general VAR, including higher-order lags of x_{t-2} and x_{t-3}, is considered below in the results but the form in equation (1) is general enough to describe the process of model validation, estimation, and hypothesis testing, that is documented in this section.

Estimation

Given a set of observations on x_t, equation (1) can be formulated as a system of equations in the form of Zellner's (1960) seemingly unrelated regression (SUR). In this case, each equation in a VAR has the same set of regressors and it is well known that parameters in each equation implicit in the system (1) can be estimated by ordinary least-squares without losing efficiency relative to generalized least-squares. The S+Finmetrics module has a routine for estimating VAR models.

Diagnostic tests

Statistical properties of ε_t in equation (1) are important, both in terms of model validation and in the distributional assumptions behind each hypothesis test. In particular, the results of statistical tests given below do not reject the assumption of a multivariate normal distribution (Shapiro-Wilk 1965) and do not present significant levels of autocorrelation in the process (Ljung and Box 1979). Other tests, for the presence of unit roots (Said and Dickey 1984; Kwiatkowski, Phillips, Schmidt and Shin 1992), are concerned with bounds on diagonal elements of *A* to rule out nonstationary behavior in the model. Results of unit root tests are presented below, in Section 4, and do not reject a stationary null in the series of price indices that are used for the analysis in this report. Likewise, production levels and export quantities of Alaska king crab are compatible with a stationary model, but the time series of U.S. import quantities of king crab is clearly not stationary. Since nonstationary data can produce spurious regressions, stationary data are an important prerequisite for the methods described in this section. Therefore, the results described below are based on price indices alone and the nonstationary series of import quantities is excluded from the statistical analysis in this report. The Shapiro-Wilk and Ljung-Box tests are implemented in S+, and both references for unit root tests are available in the S+Finmetrics module. Note that the first unit root test is the Augmented Dickey-Fuller, which starts from a unit root null, whereas the second, known as the KPSS test, is based on a stationary null.

Forecasting and Granger Causality Tests

A fundamental question that a VAR model can be used to address is how useful some variables are in forecasting other variables in the system. In fact, dynamic relationships in a VAR model are meant to be interpreted in terms of forecasts. Define the conditional expectation $E_t(\varepsilon_{t+j}) \equiv E(\varepsilon_{t+j} \mid x_t, \varepsilon_t)$. By assumption, $E_t(\varepsilon_{t+j}) = 0$ for all $j > 0$.

In a bivariate VAR, the off-diagonal terms of matrix *A* in equation (1) represent the influence of lagged values of one variable on the dynamics of the other. For example, the bivariate version of equation (1) is represented explicitly by the system

$$
\begin{aligned}
x_{1t} &= c_1 + a_{11}x_{1t-1} + a_{12}x_{2t-1} + \varepsilon_{1t}, \\
x_{2t} &= c_2 + a_{21}x_{1t-1} + a_{22}x_{2t-1} + \varepsilon_{2t}.
\end{aligned} \tag{2}
$$

In the bivariate case, each *k*-step ahead forecast of $E_t(x_{t+k})$ depends only on the vector x_t and matrix powers of *A*, which is called the Markov condition. Therefore, an off-diagonal term $a_{ij} = 0, i \neq j$, in the system (2) implies that variable *j* is not helpful in forecasting variable *i*, or in the terminology of time series econometrics, variable *j* does not Granger cause variable *i*. Explicitly, x_2 fails to Granger cause x_1 if $a_{12} = 0$, and conversely, x_1 fails to Granger cause x_2 if $a_{21} = 0$. Granger causality tests are easily conducted by using the Wald test statistic in S+.

The Markov condition and statements about Granger causality can be easily seen to hold in multivariate VAR models and models with higher-order lags by following a procedure of recursive substitution using equation (1). In the multivariate case, Granger causality fails to hold in one direction if the matrix *A* is upper (or lower) triangular, and it fails to hold in both directions if the matrix is diagonal. In cases with higher-order lag variables, Granger causality fails if the matrix of coefficients for each lag are upper (or lower) triangular.

A final point about Granger causality worth emphasizing is that statements regarding its direction are not necessarily related to any notion of physical causation. For example, it is entirely possible that an economic variable such as prices could Granger cause a physical variable such as weather. In this case, a physical interpretation of causation would be nonsense. Instead the presence of Granger causality can be explained by forward looking behavior by rational agents, who may have an economic incentive to forecast certain types of weather events, and thus, changes in their behavior in response to these forecasts could have significant effects on prices. In such circumstances, prices may not fail to Granger cause the weather.

Chow's Test for Structural Breaks

The presence of structural breaks is an important issue in time series econometrics. An obvious example from macroeconomics is the business cycle. The simplest type of test in this situation involves a known date at which a break possibly occurred. Chow (1960) described a simple and flexible test statistic, based on an ordinary least squares (OLS) linear regression model, that applies even in situations where only 1 or 2 additional observations are available following the date of a possible break, which is the situation currently with crab rationalization.[1] The basic idea behind Chow's test is to compare predictions of the linear regression model, conditional on data from before the possible break, with the additional observations using the squared-difference as a test statistic. Unlike other statistical tests that are cited in this report, the Chow test is not available in S+. Consequently, a version of Chow's test for the work described in this report was developed and programmed in S+ by the author, and it is documented here for review.

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[1] Rea (1978) demonstrates that there is a source of indeterminacy in the Chow test when the number of additional observations is less than the number of parameters in the model for the period after a possible structural break. This indeterminacy can be derived explicitly for each equation in a bivariate VAR model and is not a concern here. In this case, estimates are represented by a point on a plane, the set of indeterminate points form a line in that plane, and the original (pre-break) estimates are a point on that line. If the post-break estimates are significantly different, and the direction of change is arbitrary, then almost surely, the post-break estimates are not on that line.

Since OLS estimation of each equation in the system (2) is efficient under conditions assumed here, Chow's procedure can be applied directly to each. Let α_i denote a column vector that contains all of the parameters, including the constant term, in equation $i = 1, 2$ from the system in (2). From (2), the dimension of each α_i is 3. However higher order lags in a bivariate VAR are considered in the results below. In this case, the dimension of each α_i is $k = 2l + 1$, where l denotes the number of lags in each equation.

Suppose there are initially $t = 1, \dots, T$ observations on each variable in the system. However with a VAR, only $n = T - l$ observations are available for estimation because lag variables in each equation must be filled. Assume $n > k$ which is equivalent to $T > 3l + 1$ in a bivariate VAR. A set of *k*-dimensional column vectors can be constructed that contain the data that form the regression equation for each *t*. Each vector has a one in the first position that corresponds to the constant term in each α_i. The first vector in the set has variable pairs (x_{1t}, x_{2t}) that correspond to the first $t = 1, \dots, l$ observations. The second vector has variable pairs that correspond to the next $t = 2, \dots, l + 1$ observations, and so on until the *n*-th vector contains pairs from $t = T - 1 - l, \dots, T - 1$. Let X_n denote the $n \times p$ matrix that results from stacking these vectors, and let $y_{i|n}$ denote the column vector of observations, x_{it}, from $t = l + 1, \dots, T$. Let $\hat{\alpha}_{i|n}$ represent the OLS estimate from the regression of $y_{i|n}$ on X_n.

With an additional *m* observations, a continuation of the stacking procedure from above defines an $m \times p$ matrix, X_m. These additional observations are specified by the model

$$y_{i|m} = X_m \alpha_{i|m} + \varepsilon_{i|m}. \tag{3}$$

By assumption $\varepsilon_{i|m}$ is normally distributed with covariance matrix $\sigma_i I$, identical to the process for $\varepsilon_{i|n}$. This assumption is important but not the subject of testing here.

Chow's test is based on the value of the prediction error defined by the vector of differences $d = y_{i|m} - X_m \hat{\alpha}_{i|n}$. Hence, its expected value is

$$E(d) = X_m \alpha_{i|m} - X_m \alpha_{i|n}. \tag{4}$$

Let $s_{i|n}$ denote the (unbiased) standard error from the *n* observations on equation *i* and let *H* denote the hat-like matrix $X_m (X_n' X_n)^{-1} X_m'$, where a prime denotes the matrix transpose operation. It can be shown that under the null hypothesis $\alpha_{i|n} = \alpha_{i|m} = \alpha_i$ the statistic

$$\frac{d'(I + H)^{-1} d}{m s_{i|n}^2} \tag{5}$$

follows an $F(m, n\text{-}k)$ distribution. If $m = 1$, then H and d are scalars and the test is based on the prediction interval for one additional observation. In this case, the distribution under the null hypothesis is $F(1, n\text{-}k)$ and equation (5) reduces to the ratio

$$\frac{d^2}{(1+H)s_{i|n}^2}. \tag{6}$$

Both versions, in equations (5) and (6), are used in the results below.

3. Data

Price series used in this report are broadly defined as indices of real values paid, or received, divided by the amount traded, or produced, in the 16 years from 1991-2006. These price indices are taken as industry-wide averages. Real values were calculated using the U.S. producer price index for the item 'unprocessed and packaged fish' (i.e. series WPU0223 from U.S. Bureau of Labor Statistics http://www.bls.gov/ppi). The last year of data, 2006, is based on the most recent year of COAR data that was available to the author at the time analysis for this report was initiated, in spring 2008. The first year of data, 1991, was selected based on the author's confidence in reliably linking COAR data with Intent to Operate (ITO) records, CFEC fish tickets, and other sources (T. Hiatt, pers. comm.). Since the U.S. trade statistics for king crab go back to 1983, an analysis that uses longer time series may be feasible in the future.

Comparable data requires that selected process and product codes in COAR match categories that are relevant to king crab in the Harmonized Commodity Description and Coding System (HS) for import data. Only 3 categories in the HS-10 system, the finest resolution available in the U.S. Merchandise Trade Statistics, specifically identify king crab, and these 3 provide no further detail about species. These 3 are frozen king crab (not elsewhere specified or indicated), prepared king crab meat (frozen), and prepared king crab meat (in airtight containers). The latter pair appears to have been added recently to the HS-10 system, and almost all U.S. king crab imports fall into the frozen king crab category. Thus, data on U.S. imports are comparable to data with the process code 'frozen' in COAR. Regarding species composition, U.S. imports are believed to be composed mainly of red king crab from Russia, with smaller amounts from Norway, and it is unknown how much of U.S. imports are derived from Bering Sea, versus Barents Sea, stocks. The most direct comparison with U.S. imports is the red king crab fishery in Alaska. However comparisons over time with blue, and golden, king crab are interesting and COAR data on all 3 species are presented next.

Wholesale Prices from COAR

Files containing COAR production data were retrieved from the Pacific States Marine Fisheries Commission Alaska Fisheries Information Network (AKFIN) in spring 2008. Since COAR records are given with processor identification (PID) codes, it is important to realize that there is not a 1-1 relationship between processors and PID codes, and in some cases, an individual PID code may even be associated with different processors over time. Even though aggregated data are used in the time series analysis described in this report, data quality considerations motivate treating these data in a disaggregated format in the construction of these aggregates, to identify unlinked (i.e. orphan) records, determine the number of distinct processing units in the sample, and calculate other essential statistics. Therefore, a bridge between PID codes and processors for each year was needed to stratify the production data among processing units. The Alaska Department of Fish and Game (ADFG) generously provided that bridge with lists of processors (based on federal EIN) that recorded landings for species codes 921 (red), 922 (blue), and 923 (golden), king crab in the years 1991-2006.[2] In particular, these lists associate each processor with a set of PID codes, for each year, under which king crab was bought or sold. Numbers of distinguishable separate processors in each year are listed in Table 1.

Table 1: Number of Separate Processors (N) with King Crab Production in COAR 1991-2006.

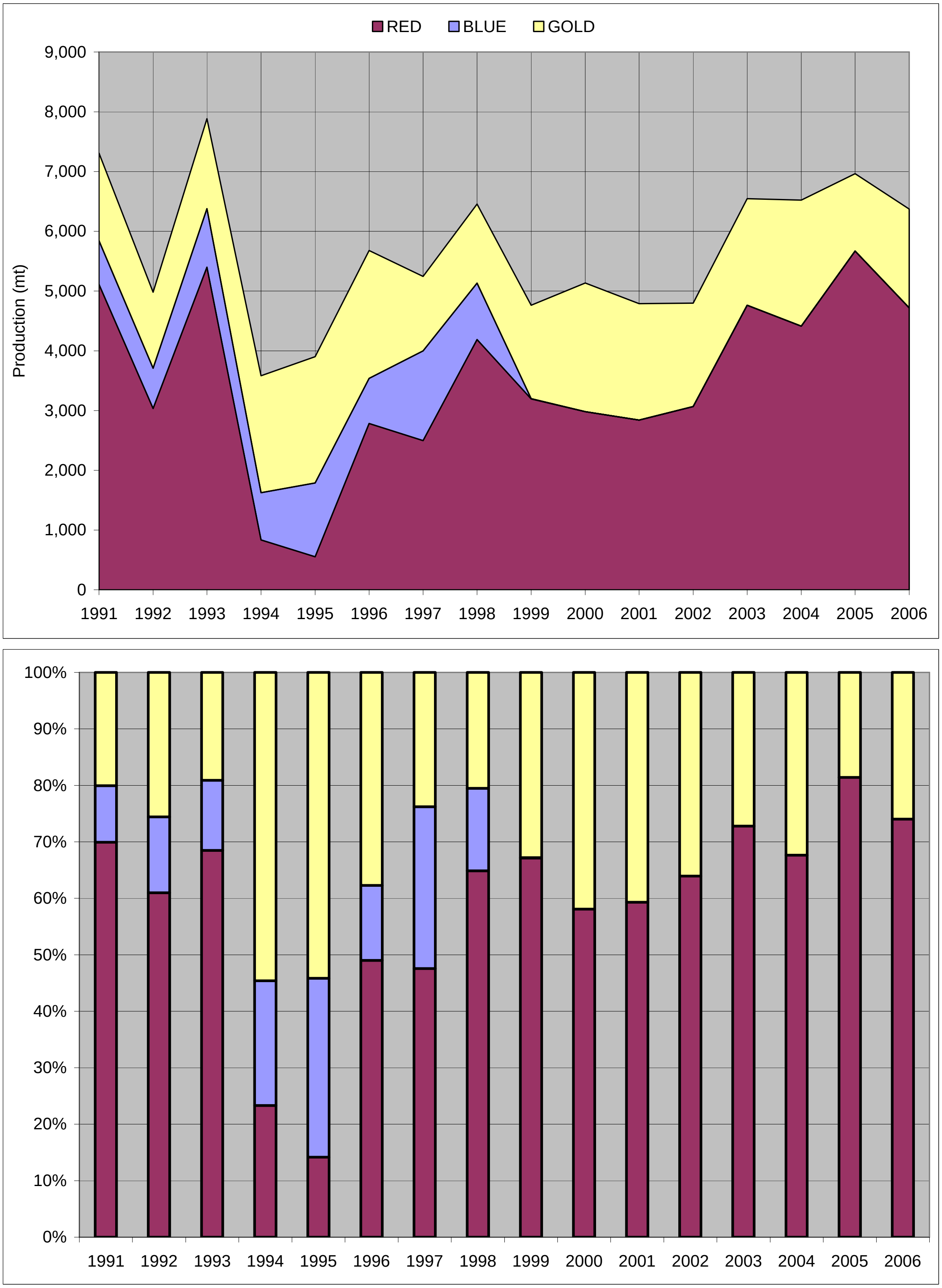
	RED(N)	BLUE(N)	GOLD(N)
2006	9		10
2005	13	1	10
2004	13		11
2003	22	1	14
2002	22	1	13
2001	23	1	12
2000	17	2	13
1999	20	3	13
1998	16	12	11
1997	19	13	13
1996	22	11	11
1995	22	13	14
1994	19	11	11
1993	22	14	13
1992	20	12	11
1991	24	9	10

Summaries of COAR production data in each category were computed based on the ADFG processor lists using programs written by the author in Perl, a high-level dynamic programming language with powerful text processing capabilities that make it ideal for working with large text files (Wall, Christiansen, and Orwant 2000). These COAR summaries include king crab produced under all process and product codes.[3]

[2] The author thanks Mike Plotnick for running these queries, providing the lists in a nice useful format, and advice on interpreting COAR and ITO databases. Processors with production of Tanner crabs were also included in the lists, but a time series analysis of that data was not ready in time for this report, and it is planned for a future report.

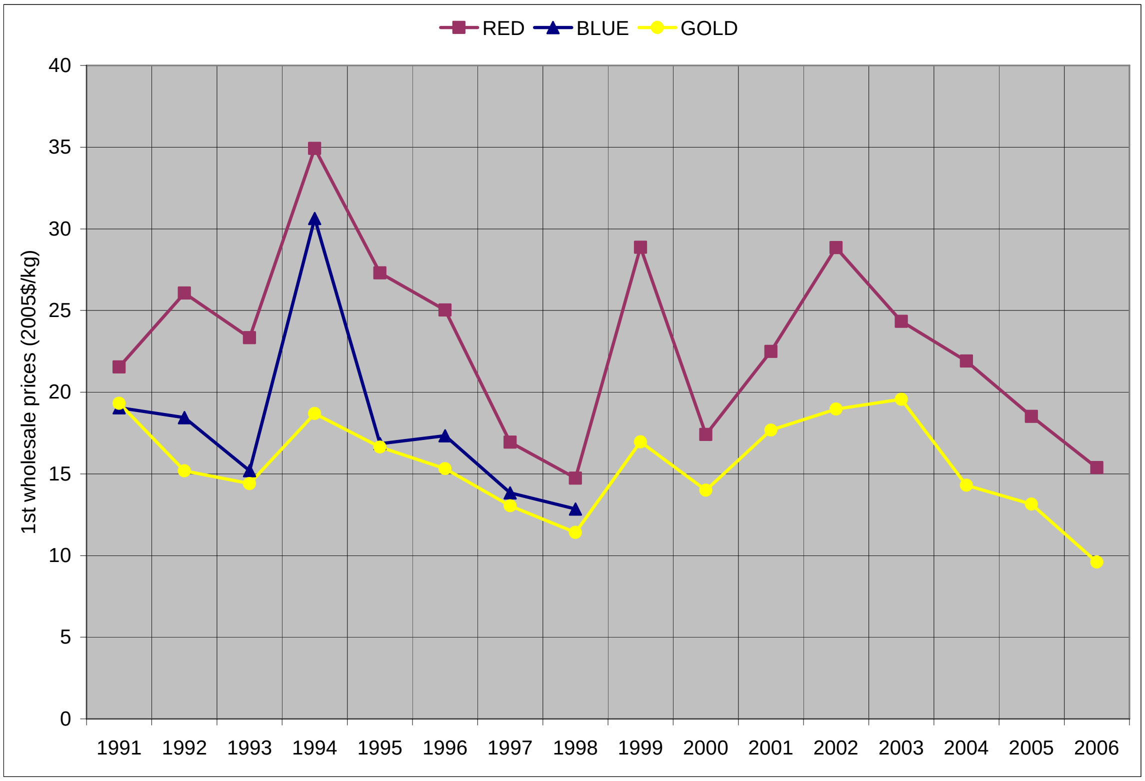
[3] The process codes in COAR for a common commodity (cooked and frozen crab) are ambiguous, which resulted in an ADFG whitepaper on the subject (Shirley 2005). The recommendation there was to indicate 'cooked' if the crab was cooked before freezing. However prior to 2005, essentially all king crab production in COAR was processed under the code for 'frozen' despite the fact that a substantial amount (perhaps most) was cooked and then frozen. Since 2005 the fraction of king crab recorded in COAR as 'cooked' has increased, and was close to 50% in 2006. However it is unknown how much of that increase reflects actual changes in the processing of king crab post-rationalization and how much is due to changes in recording behavior. In addition, several king crab records in COAR have process or product codes that do not make sense, including one with more than 10% of total production in a year. These 2 sources of uncertainty in the process and product codes favor an inclusive treatment. Another justification for aggregating these codes is to reconcile COAR production levels with U.S. exports of king crab, which is addressed below.

Figure 1: Red, Blue, and Golden, King Crab Production from COAR, 1991-2006.



Data fields in COAR files vary by year but only a subset of these, which are available for all years from 1991-2006, are relevant here: species code, process code, product code, net pounds (net_lbs), and wholesale values in current dollars (ws_val).[4] In the production summaries, net pounds of production were converted to metric tons (mt), and wholesale values to thousands of real (2005) dollars. With these changes in units, dividing wholesale values by production quantities gives a COAR price index (COARPI) in real dollars per kilogram (2005$/kg).
Data displayed in Figure 1 are used with real COAR wholesale values to form indices of wholesale prices for each species of king crab. These price indices are displayed in Figure 2. Red king crab is seen to be the most valuable per unit weight over weight, except in a few years after 1999 which are not important (and not displayed due to confidentiality restrictions based on a rule of 4) because only negligible amounts of blue king crab production appeared in COAR for these years. A recent downward trend in prices is evident but it is not unprecedented, a decline of even greater magnitude occurred after 1994 for red king crab, the low value in 2006 was also reached in 1998, and in general, the price index for it is volatile. Consequently, there does not seem to be a clear trend in price indices for king crab since 1991.

Figure 2: Real Wholesale Prices for King Crab Production from COAR, 1991-2006.



U.S. Imports and Exports from the Trade Policy Information System

The Trade Policy Information System (TPIS) is a web-based retrieval tool for accessing U.S. and United Nations trade data that is made available to federal government employees by the

[4] References for ADFG codes and COAR booklets can be found online at www.adfg.state.ak.us.

International Trade Administration in the U.S. Department of Commerce.[5] The author used TPIS to query HS-10 level detail in the U.S. Merchandise Statistics, which are collected by the U.S. Census Bureau. There are 3 HS-10 codes that link specifically to king crab: ‘King crabs, frozen’ (#0306144010), ‘King crabmeat, prepared in airtight containers’ (#1605102010), and ‘King crabmeat, prepared frozen’ (#1605104002). The latter pair (i.e. #1605…) are probably recent additions to the HS-10 system (which is updated periodically), and these categories are associated with negligible quantities over the time period analyzed in this report. In terms of COAR code descriptors, U.S. trade data identify a single process, frozen, which presumably consists primarily of sections or whole crab but may also contain unknown amounts of crabmeat or other products that involve further processing. As noted above, there is an ambiguity in process codes with respect to king crab in COAR production data, and also in trade data, because both cooking and freezing may occur. In addition, HS-10 import and export data do not identify the particular species.

Unlike imports, the composition of U.S. exports has probably varied over time, and even though exports are not the subject of this report, it is worth briefly comparing export levels from TPIS with production levels from COAR. This comparison, between total king crab production (red, blue, and golden) and king crab exports (which implicitly includes these 3 species in unknown amounts), is presented in Figure 3 in terms of both physical units and monetary value. The first set of comparisons is between total production and export levels, using the ratio of COAR production divided by TPIS export volume (both in metric tons). The second set of comparisons is between real wholesale values from COAR, divided by TPIS real export values (both in 2005 dollars). For the latter, export values are taken as ‘Free Alongside Ship’ (FAS), meaning net of transport margins. Figure 3 indicates that the year 1994 is a bounding case where total production in COAR for all 3 species just meets the export volume recorded in the U.S. trade statistics for that year.

Both sets of statistics, exports and production, are based on the same calendar year, and thus, the latter should exceed the former if both sets are to be believed. Since the values in 1994 are suspiciously close, errors in one, or both, series are reasonable concerns. However a consistent bias in levels should not have a substantive effect on the model and tests described in Section 2. In addition, there is a noticeable difference in 1994 between the ratios of export volume divided by total production, compared to that of export value divided by wholesale value, but nonetheless this difference in 1994 is comparable to other years (e.g. 1999, 2003). In general, the difference between these ratios has varied over time, reflecting 2 types of changes: those in prices and in the species composition of exports. In most years, the ratio in quantities is greater than the one in values which implies that the average value (over all species) of king crab was greater in the U.S. compared to the average price that Alaska producers received on global markets. This result implies either that world prices were lower, or that higher value king crab (e.g. red) was consumed, than on average in the U.S.

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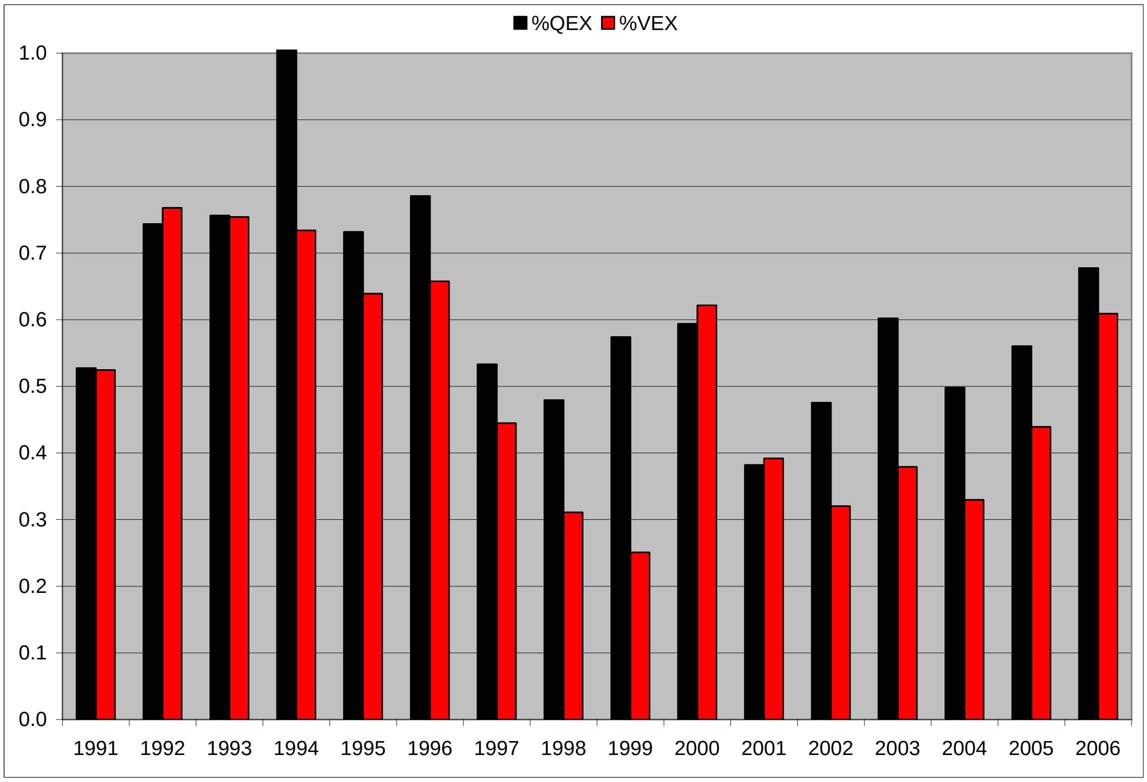
[5] In addition, NMFS Office of Science and Technology administers a trade database (http://www.st.nmfs.noaa.gov/st1/trade) with data from the Foreign Trade Service in the U.S. Census Bureau. The NMFS site is better suited for faster queries that do not require direct access to HS-10 level data. Similarly, the Foreign Agriculture Service in the U.S. Department of Agriculture has a website with trade data (http://www.fas.usda.gov), which provides a good source for HS-10 category descriptions and also a good source of HS-10 data. However TPIS is more efficient at generating formatted files that can be processed directly to generate time series of exports and imports at the HS-10 level.

Figure 3: U.S. Exports of Frozen King Crab as a Fraction of COAR Production (QEX) and Wholesale Value (VEX) of King Crabs, 1991-2006.



Data on the total physical volume of king crab imports (from TPIS), and COAR production net of the total physical volume of TPIS exports are displayed in Figure 4. The latter quantity represents, perhaps imperfectly due to comparability issues with respect to COAR and TPIS or re-exported crab returning to the U.S., the amount of domestic production that is consumed in the U.S. The 'flood' of Russian king crab into the U.S. after 2004 that is mentioned in the introduction is apparent in Figure 4: U.S. imports of king crab increased by approximately 200% from levels in, and before, 2004. At this stage, questions arise as to whether the temporal pattern of imports in Figure 4 presents a problem for the time series analysis described in Section 2. Visually, the sharp increase in imports after 2004 certainly does not appear to be stationary and it is not surprising that both diagnostic tests for this situation that are referenced in Section 2 reject the hypothesis that the time series of king crab imports is stationary. Therefore this time series violates a fundamental assumption in the VAR framework described above. A suitable extension of that framework might accommodate the time series for imports, but those techniques are beyond the scope of this report. Quantities are directly excluded from the time series analysis described in this report, and only dynamic relationships between price indices based on COAR and TPIS imports are considered.

Figure 4: U.S. Import Volume (TPIS) and Production Net of Exports (NETCOAR), 1991-2006.

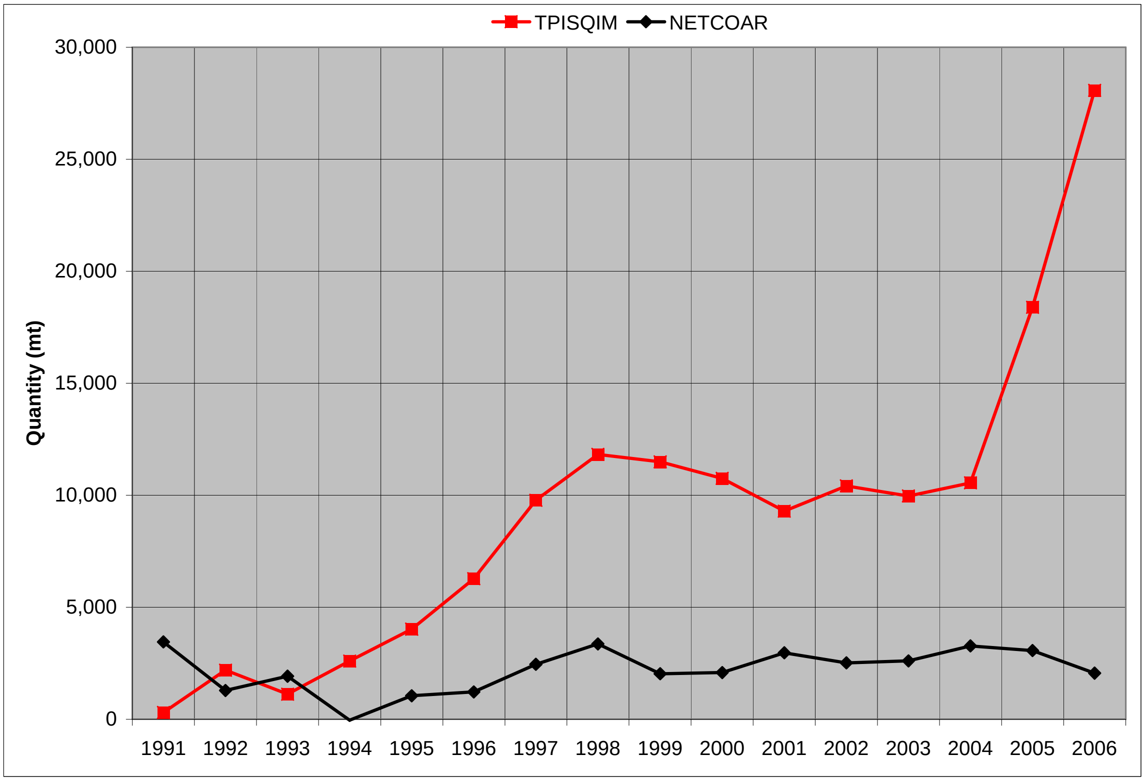


Figure 5: Price Indices for COAR wholesale, TPIS Exports, and TPIS Imports, 1991-2006.

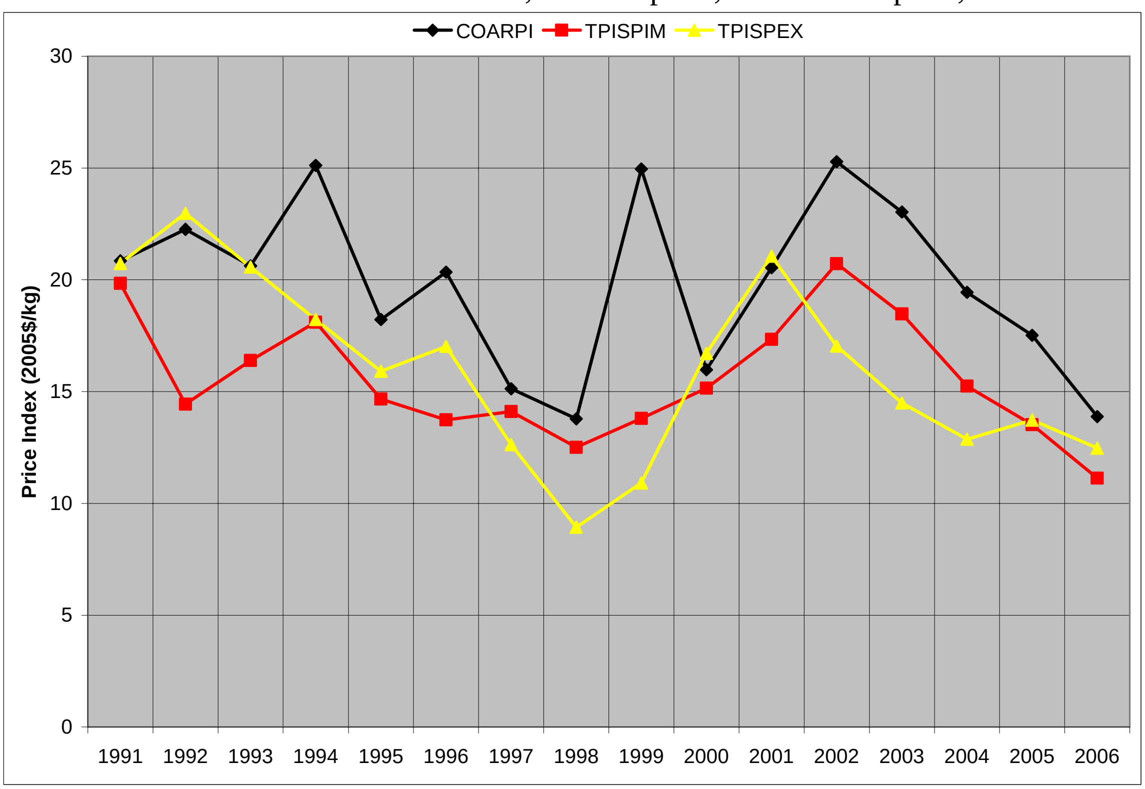


Figure 5 displays time series of TPIS imports and COAR price indices. The price index for TPIS imports uses the 'Customs' value of imports in TPIS, which is the value of a commodity that is assigned upon entry into the U.S., and is formed by dividing this value for each year by the quantity imported in that year. A price index for TPIS exports, based on FAS-values, is also displayed in Figure 5 for comparison.

All 3 series in Figure 5 decline after 2001, and nearly converge. In general, the range of these 3 variables fluctuates over time from a high in 1999, driven by a high value in the wholesale price index from COAR and an unusually low period in the TPIS price index for imports of king crab. A potentially significant feature is the simultaneous decline of all 3 series in Figure 5 after 2002, but it is worth noting that this decline in prices began before the sharp increase after 2004 in the volume of U.S. king crab imports.

4. Results

A generalization of the first-order VAR in (2), including second- and third-order lag variables, was analyzed and results for all 3 lag lengths are reported in this section. For convenience, the first-, second-, and third-order VAR models are denoted by VAR(1), VAR(2), and VAR(3), respectively. For reference, a VAR(3) has 8 parameters to estimate, and 13 years of data from 1991-2006 are available for estimation. A fourth-order VAR has 18 parameters, but only 12 years of data can be used, and therefore estimation is indeterminate here for any VAR of order greater than 3.

The analysis reported here follows the advice of Zivot and Wang (2003) in using model selection criteria to determine lag length in a VAR. This text lists the 3 most common information criteria: Akaike (AIC), Schwarz-Bayesian (BIC), and Hannan-Quinn (HQ). Results for these criteria are presented in Table 2. In particular, the goal is to select a lag length that minimizes an information criterion. Here the results are ambiguous because 2 criteria (AIC and HQ) favor a VAR(2) but the BIC favors a VAR(1).[6]

Table 2: Information Criteria for VAR Models of Price Indices from COAR and TPIS Imports.

	VAR(1)	VAR(2)	VAR(3)
AIC	126.8	125.7	132.7
BIC	130.2	131.4	140.7
HQ	126.1	124.6	131.1

Since the model selection criteria described above are not the only indicators, and are not definitive in this case, a complete set of regression results for each of the 3 models is presented in Table 3.

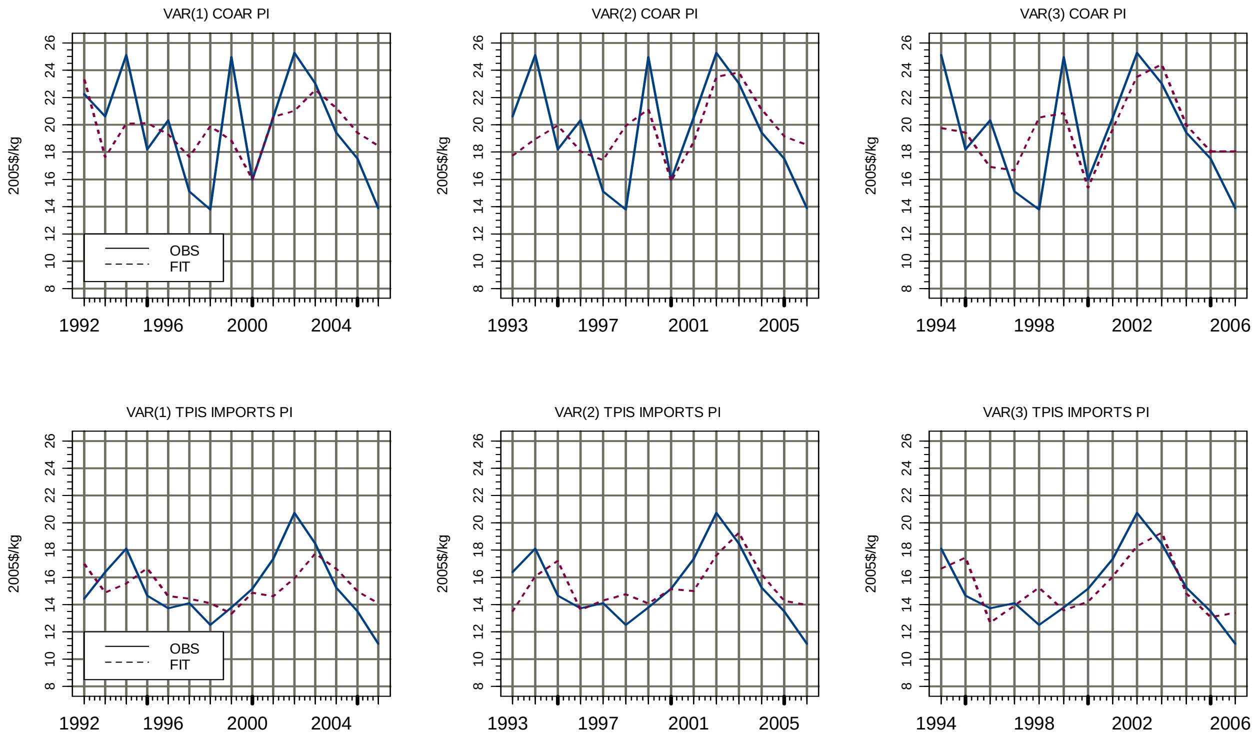
[6] Hamilton (1994, p.297) describes a standard likelihood ratio test that is simple to perform, with an asymptotic chi-squared distribution, for determining lag length in a VAR with normal error terms. This test of a VAR(1) against a VAR(2) has a p-value of 0.06, whereas the log-likelihood value of a VAR(3) is very close to a VAR(2), and the p-value for the latter test is 0.90. Thus, results of the likelihood ratio test appear to be consistent with those in Table 2.

Table 3: Regression Results for VAR Models of Price Indices from COAR (xp) and TPIS Imports (xm).

	VAR(1)		VAR(2)		VAR(3)	
	xp	xm	xp	xm	xp	xm
(Intercept)	11.791	6.958	14.588	8.610	16.163	8.897
(std.err)	6.796	4.291	9.333	5.428	13.800	6.955
(t.stat)	1.735	1.622	1.563	1.586	1.171	1.279
xp.lag1	-0.363	0.090	-0.636	-0.049	-0.784	-0.128
(std.err)	0.347	0.219	0.453	0.264	0.605	0.305
(t.stat)	-1.047	0.410	-1.403	-0.185	-1.295	-0.420
xm.lag1	0.963	0.411	1.392	0.865	1.787	1.206
(std.err)	0.503	0.318	0.721	0.419	1.052	0.530
(t.stat)	1.914	1.293	1.930	2.063	1.699	2.274
xp.lag2			-0.466	-0.136	-0.454	-0.011
(std.err)			0.433	0.252	0.635	0.320
(t.stat)			-1.076	-0.539	-0.715	-0.033
xm.lag2			0.349	-0.187	-0.007	-0.663
(std.err)			0.622	0.362	1.037	0.523
(t.stat)			0.561	-0.517	-0.007	-1.269
xp.lag3					-0.061	0.098
(std.err)					0.544	0.274
(t.stat)					-0.112	0.357
xm.lag3					0.097	-0.082
(std.err)					0.813	0.410
(t.stat)					0.120	-0.199
R^2	0.235	0.246	0.308	0.434	0.379	0.616
Adj.R^2	0.107	0.120	0.000	0.183	-0.242	0.232

Each column in Table 3 corresponds to a single equation in one of the models, and summary diagnostics for each are given by R-Squared, and an adjusted R-Squared statistic, as reported by the S+Finmetrics software. In addition to coefficient estimates, the software provides standard errors and t-statistics to evaluate the significance of individual parameters in each equation. A comparison of observed and fitted values for each VAR model is presented in Figure 6.

Figure 6: Observed and Fitted Values for VAR Models of Price Indices from COAR and TPIS Imports.



The next set of results is aimed at testing key assumptions in the VAR framework, based on the diagnostic tests described in Section 2. There, 2 tests are cited to determine whether data are compatible with a stationary model. One is probably the most popular unit-root test, Augmented Dickey-Fuller (ADF), which is based on a null hypothesis that data are nonstationary. The other, KPSS, is based on a stationary null. For the latter, the software reports a value of the test statistic, and only whether it is significant at a 1%, or 5%, level. Test statistics and p-values for both unit-root tests (up to the level reported by the software for the KPSS test) are presented in Table 4. Note that the KPSS test does not depend on lag length (or at least it is not an option in the S+Finmetrics function) and its values for each equation are repeated under each VAR model to compare with ADF test results. In all but 1 case, neither hypothesis is rejected by results in Table 4. In that 1 case, the ADF test rejects the null of nonstationary data. In other words, the stationary null was not rejected, and in 1 case, the nonstationary null was rejected (5%-level).

Table 4: Augmented Dickey-Fuller (ADF) and KPSS Unit Root Tests of Price Indices from COAR (xp), and TPIS Imports (xm).

	VAR(1)		VAR(2)		VAR(3)	
	Xp	xm	xp	xm	xp	xm
ADF (unit root null)	-3.169	-2.085	-2.045	-1.704	-1.576	-1.901
p.value	0.043	0.252	0.267	0.408	0.466	0.322
KPSS (stationary null)	0.137	0.107	0.137	0.107	0.137	0.107
p.value	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05

Properties of the residuals from each fitted VAR model are quantified in Table 5 using the diagnostic tests for normality and autocorrelation that are described in Section 2. In addition, the fitted residuals are presented graphically in Figure 7 and Figure 8, for the COAR price index (PI) and TPIS Imports PI, respectively. Plots in each column correspond to a single model (i.e. lag length). The first row of plots shows the fitted residuals for each model as a time series. The second row displays histograms of these residuals. The autocorrelation function (with 95% confidence limits about zero) for each model is plotted in the third row. In the fourth row, normal quantile-quantile (QQ) plots for each model are expressed, which are scatterplots of standardized empirical quantiles of each set of residuals against the quantiles of a standard normal distribution (i.e. if the residuals are normally distributed, then the quantiles will lie on the 45 degree line).

Table 5: Tests of Residuals from VAR Models of Price Indices from COAR (xp), and TPIS Imports (xm).

	VAR(1)		VAR(2)		VAR(3)	
	xp	xm	xp	xm	xp	xm
Ljung-Box (Autocorrelation)	0.088	1.556	0.006	1.312	0.813	0.772
p-value	0.767	0.212	0.997	0.519	0.666	0.680
Ljung-Box (Autocorrelation^2)	0.309	0.025	0.548	1.655	0.027	3.208
p-value	0.579	0.875	0.760	0.437	0.987	0.201
Shapiro-Wilk (Normality)	0.968	0.951	0.980	0.927	0.970	0.902
p-value	0.795	0.522	0.950	0.268	0.845	0.137

Figure 7: COAR PI Residuals, Histograms, Autocorrelation Functions, and QQ Plots.

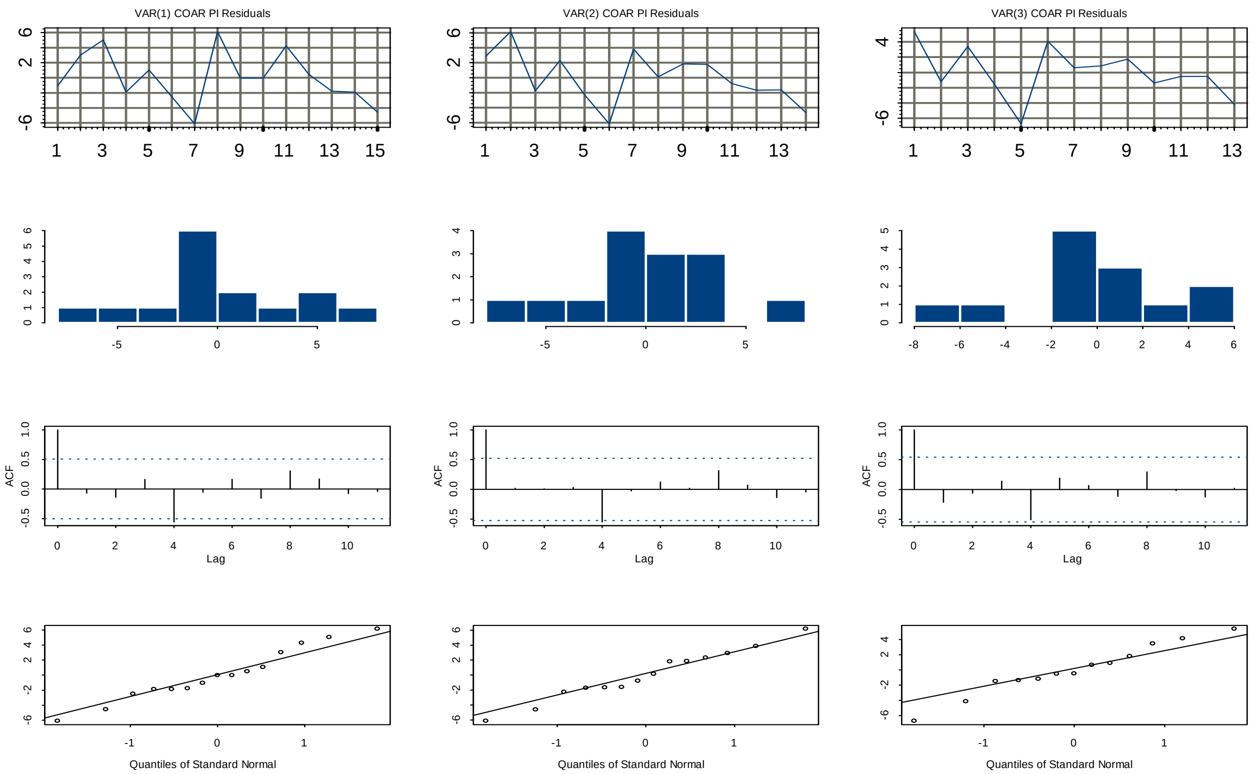
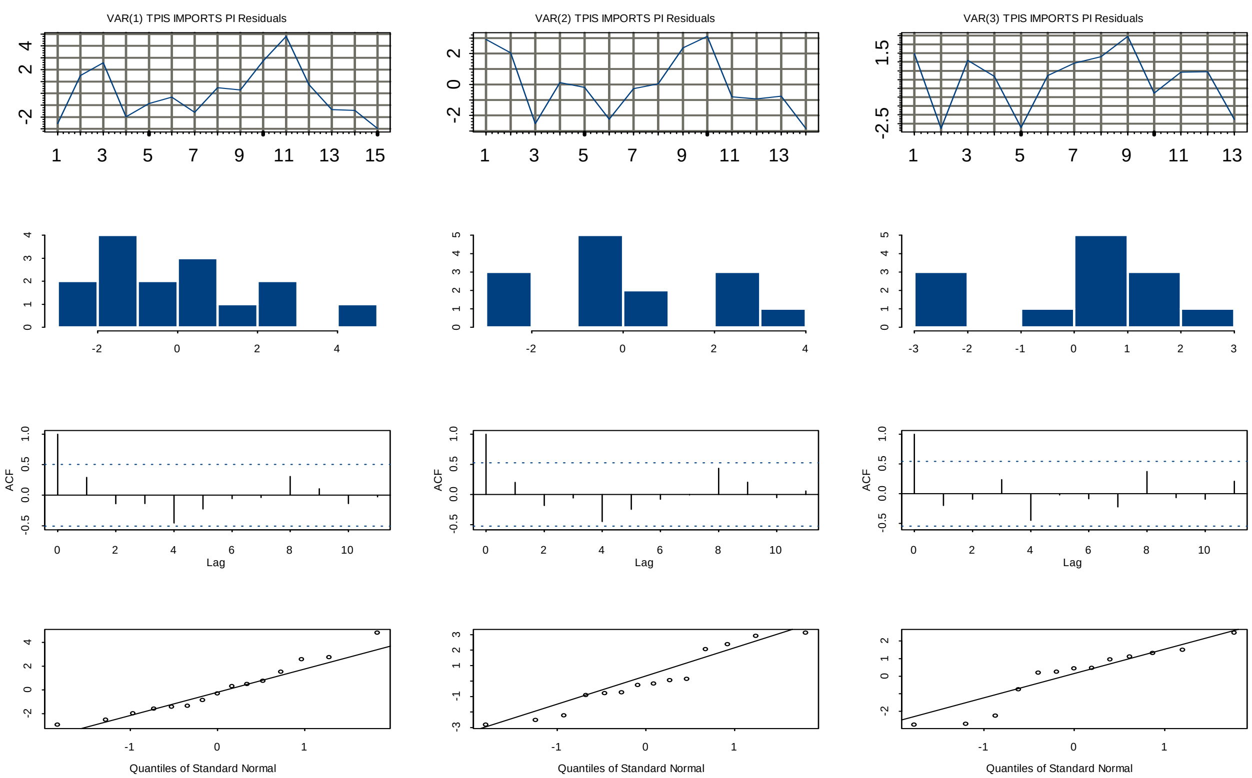


Figure 8: TPIS Imports PI Residuals, Histograms, Autocorrelation Functions, and QQ Plots.



The final set of results in this section address the 2 hypotheses raised in the introduction. One of these is that prices for U.S. imports are statistically related to wholesale prices that Alaska processors receive for king crab. The other is that crab rationalization represented a structural break in the fishery that may have affected prices for king crab. In the former case, results of Granger causality tests, carried out using the Wald statistic in S+, are presented for each VAR model in Table 6. According to these results, the COAR price index is marginally helpful in forecasting import prices only in the first-order VAR. Otherwise, there is not significant evidence of a dynamic relationship between domestic and import price series for king crab. In the latter case, 3 versions of the Chow tests were performed and these results are presented in Table 7. The first of these test results, Chow1(2005), compares predicted 2005 prices from a VAR model estimated using data from the period 1991-2004 to observed 2005 prices. The second test, Chow1(2006), is similar to the first except that data from the period 1991-2005 are used for estimation, and 2006 prices are used as the basis for comparison. In the third and final test, Chow2, data from 1991-2004 are used for estimation and both prices, from 2005 and 2006, are used for comparison. In particular, the first and second Chow tests correspond to the scalar version from equation (6) in Section 2 while the third is based on the multivariate version from equation (5).

Table 6: Wald Granger Causality Tests in VAR Models of Price Indices from COAR, and TPIS Imports.

	VAR(1)	VAR(2)	VAR(3)
TPIS Imports PI fails to Granger cause COAR PI	0.168	0.298	0.456
p-value	0.682	0.861	0.928
COAR PI fails to Granger cause TPIS Imports PI	3.663	3.991	3.630
p-value	0.056	0.136	0.304

Table 7: Chow Tests in VAR Models of Price Indices from COAR (xp), and TPIS Imports (xm).

	VAR(1)		VAR(2)		VAR(3)	
	xp	xm	xp	xm	xp	xm
Chow1(2005)	0.231	0.492	0.331	0.242	0.220	0.012
p.value	0.641	0.499	0.583	0.638	0.664	0.918
Chow1(2006)	1.849	1.958	1.638	1.854	1.045	1.247
p.value	0.201	0.189	0.236	0.210	0.354	0.315
Chow2	1.092	1.250	0.916	0.960	0.551	0.506
p.value	0.372	0.328	0.443	0.428	0.615	0.637

5. Conclusions

This report describes the application of vector autoregression (VAR) models from financial econometrics to time series based on prices paid for U.S. imports of king crab, primarily from Russia, and on wholesale prices for these received by Alaskan processors over the period 1991-2006. Overall, first- and second-order VAR models were found to fit the data about equally well and both models, plus a third-order model, passed diagnostic tests and satisfied other criteria. These models were then used to test 2 hypotheses, stated in the introduction, about the effects of imports and rationalization on wholesale prices. The first of these tests, for Granger causality, rejected the presence of certain dynamic relationships between wholesale and import price series, implying that neither series is helpful in forecasting the other. However the absence of these particular relationships does not necessarily imply that the 2 series are uncorrelated, it only means that correlation, if it exists, takes a simple form. For example, equations in the model for each price series are subject to random disturbances (i.e. regression equations) and the covariance of these across equations may be nonzero. In other words, the simultaneous decline of wholesale and import prices for king crab in the U.S. since 2002 can be attributed to outside factors that influenced both price series.

An important caveat to results from the first test is that import quantities were excluded from the time series analysis reported here for technical reasons, namely that the large influx of king crab imports to the U.S. in 2005 and 2006 violates an important assumption (i.e. stationary data) in the standard VAR model. An alternative explanation, raised in the introduction, is that if U.S. and Russian king crab products compete in domestic markets to a significant degree, then economic theory implies that, in simple terms, an influx of imports could cause both U.S. import and wholesale prices to decline. In fact substantial quantities of Alaska king crab, from 30% to more than 50% of total production since 2002, are consumed in the U.S. Under this alternative explanation, the magnitude of these declines would depend on price elasticities, and the cross price elasticity in particular, of demand for each product. Estimating these elasticities using a model of market demand is a reasonable research objective but requires a different model, data, and overall approach, from those utilized in this report. Nonetheless, if the cross price elasticity is small, for example because of quality differences that limit substitution among crab products from Alaska and Russia, then results from this alternative model would confirm those reported above.

The second hypothesis stated in the introduction was that rationalization of the Bering Sea and Aleutian Islands (BSAI) crab fisheries in fall 2005 led to a structural break in wholesale prices of Alaska king crab. A complication for testing the presence of a structural break in wholesale prices is that data on commercial processing of Alaska king crab are available only on an annual, calendar-year, basis but the rationalization program was implemented in mid-year. This complication was addressed by a sensitivity analysis using 3 versions of a Chow test: The first test was for the presence of a break in 2005 using only the observed value in that year, the second was for a break in 2006 using the observed value in that year, and the third was for a break in 2005 using observations in 2005-2006. None of these tests produced a significant result, which implies that rationalization has not had a detectable statistical effect on the wholesale price index for Alaska king crab. In a way, this result may not be surprising. In terms of economic theory, it seems that wholesale prices would increase only if there was a substantial change after rationalization in king crab products, or a shift in market power. In terms of production, large changes are not apparent in the data, though the composition of red king crab, compared to golden, appears slightly higher in 2005-2006 than in previous years but this effect on the overall price index for king crab appears to be relatively small. Regarding market power, the number of red king crab processors has declined since rationalization, from 13 in 2004-2005 to 9 in 2006, the minimum number since the start of the data series in 1991, but the number of golden king crab processors has remained between 10 and 14 through the entire period. In any case, it is worth noting here that a separate VAR, which was not included in the results above, did not support including Alaska production quantities as a significant factor in the equation for wholesale prices, which implies that Alaska king crab processors are price-takers on domestic and world markets.

Two final remarks, of a general nature, conclude this report. First, the length of the time series used for analysis in this report, especially the 2-years of data post-rationalization, are a limit on the statistical power of test results. As more data become available, the analysis in this report can be updated, and the results could change. Another way to boost statistical power of a short time series would be to use disaggregated data (i.e. time series for individual processors) in a panel vector autoregression (PVAR). In fact, an important caveat for the analysis in this report is the use of aggregated time series data. While the use of such data is a common practice in time series econometrics, it is well known that if certain restrictions on parameters in a model with individual time series do not hold, then the use of aggregated data in a model can result in biased parameter estimates and other problems (Hsiao 1986). There is, however, a major complication of testing these restrictions in fisheries data, namely the frequent and often autocorrelated occurrences of zero values over time for some individuals. Consequently, tests of these restrictions, known as an analysis of covariance, were not performed on the disaggregated data used in this report. In future work, a simulated maximum likelihood approach could be used to treat censored data (e.g. Lee 1999) in a PVAR but a suitable method of this type is not yet available in the econometrics literature, though it is the subject of ongoing work by the author (Dalton 2007).

The final point goes to evaluating the economic performance of BSAI crab fisheries following rationalization. In that regard, National Standard 5 of the Sustainable Fisheries Act considers economic efficiency in the utilization of fishery resources. In its simplest form, economic theory separates efficiency into terms of marginal revenues and marginal costs. A general conclusion of the analysis in this report is that, so far, marginal revenues (i.e. wholesale prices) have not been affected to a significant degree by rationalization. However that general conclusion is an incomplete and therefore uninformative statement about possible efficiency gains, or losses, in the BSAI crab fishery following rationalization. A complete economic accounting of efficiency considerations with respect to National Standard 5 will require a different type of analysis from the one described in this report, and in particular, that analysis will need to incorporate data on costs to prescribe any positive conclusions about possible changes in efficiency.

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Appendix: Results of Forecasting with VAR Models

Figure A1: Observed Values (2005$/kg) and 10-yr Forecasts 2007-2027 (index units 17-27) with 95% Confidence Bounds from the VAR(1) Model Conditional on Data from 1991-2006 (index units 1-16; import prices, xm, are first and COAR prices, xp, are second).

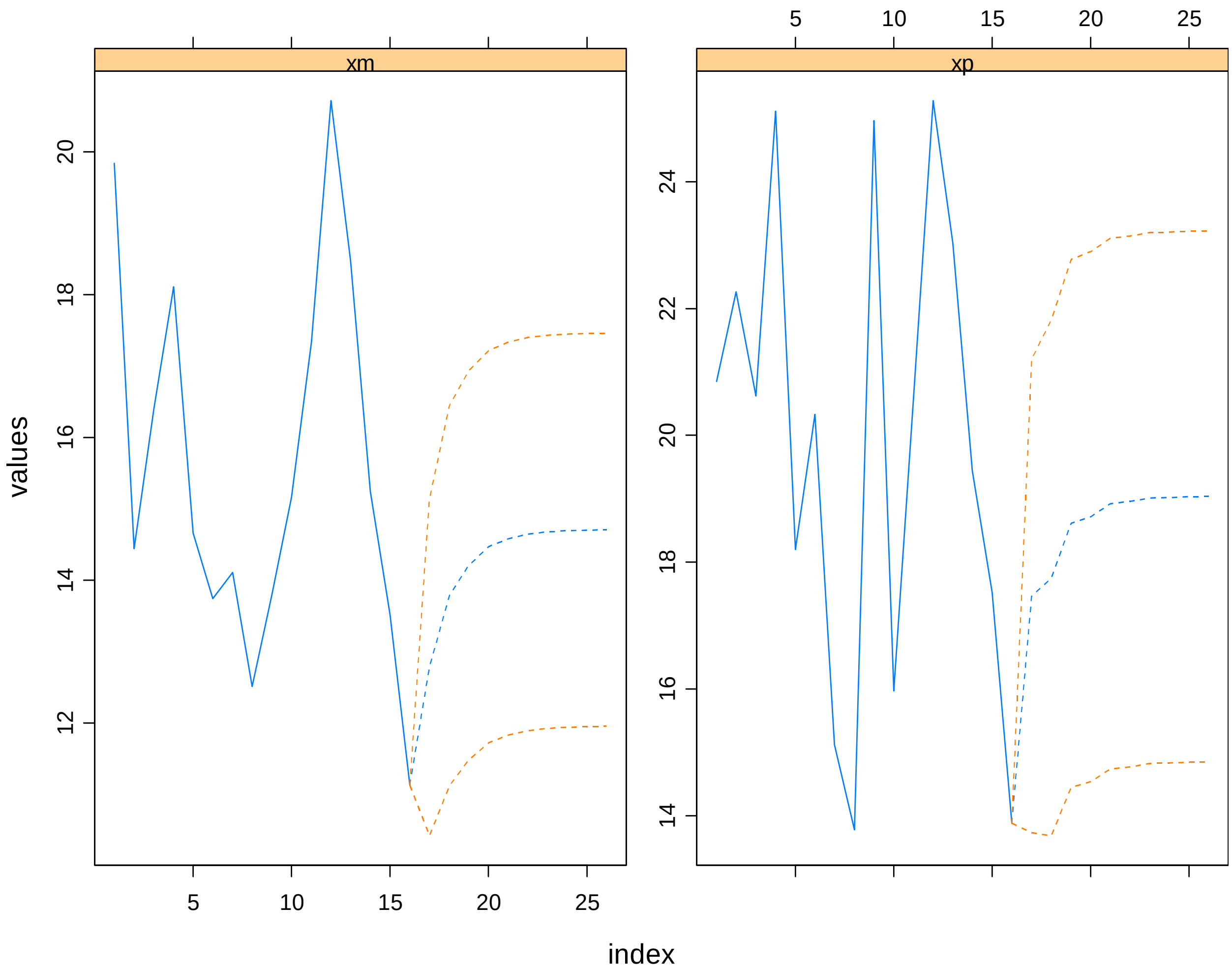

Figure A2: Observed Values (2005$/kg) and 10-yr Forecasts 2007-2027 (index units 17-27) with 95% Confidence Bounds from the VAR(2) Model Conditional on Data from 1991-2006 (index units 1-16; import prices, xm, are first and COAR prices, xp, are second).

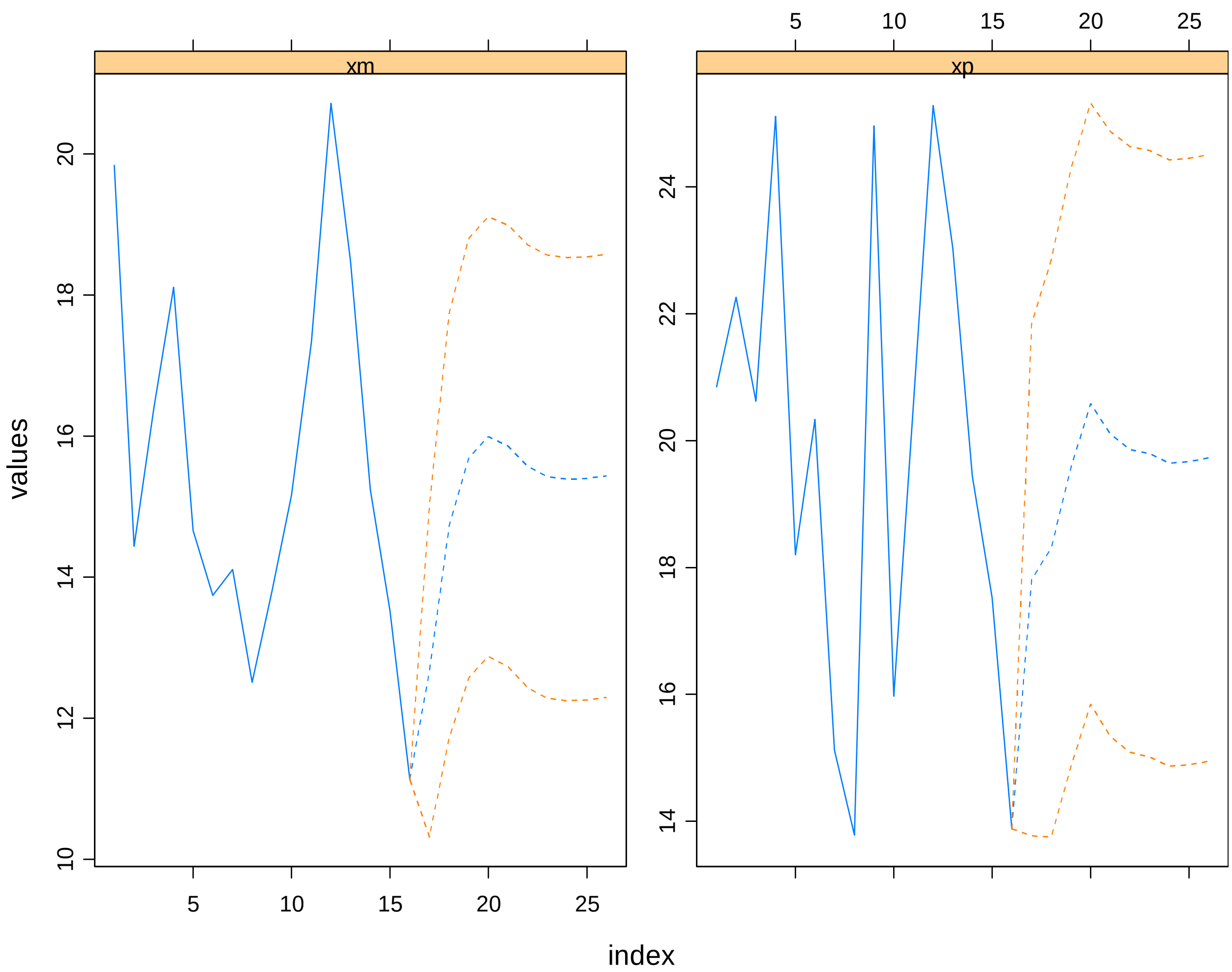

Figure A3: Observed Values (2005$/kg) and 10-yr Forecasts 2007-2027 (index units 17-27) with 95% Confidence Bounds from the VAR(3) Model Conditional on Data from 1991-2006 (index units 1-16; import prices, xm, are first and COAR prices, xp, are second).

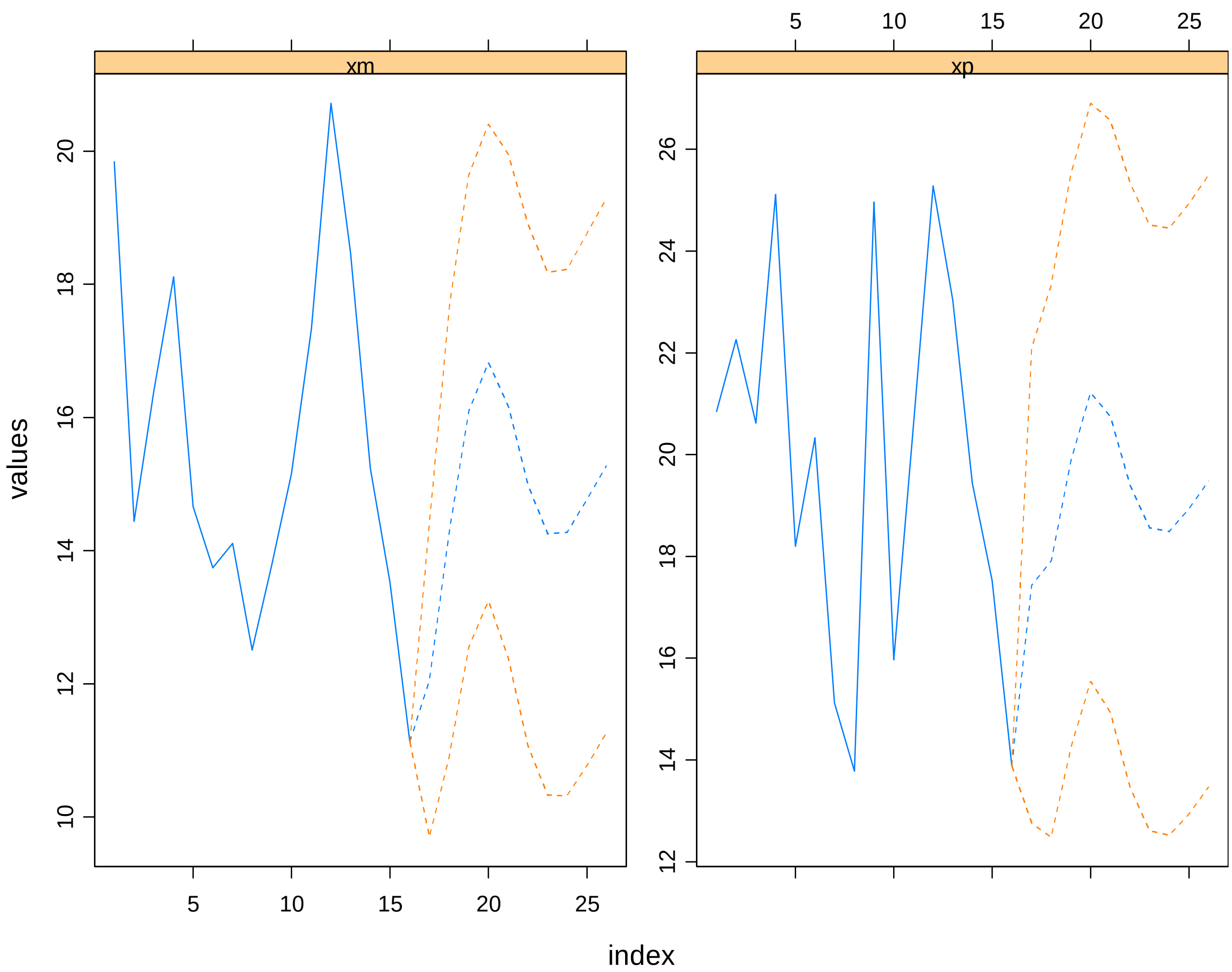

Figure A4: Orthogonal Impulse Response Functions and Forecast Error Variance Decompositions with 95% Confidence Bounds for (top to bottom) VAR(1), VAR(2), and VAR(3), Models.

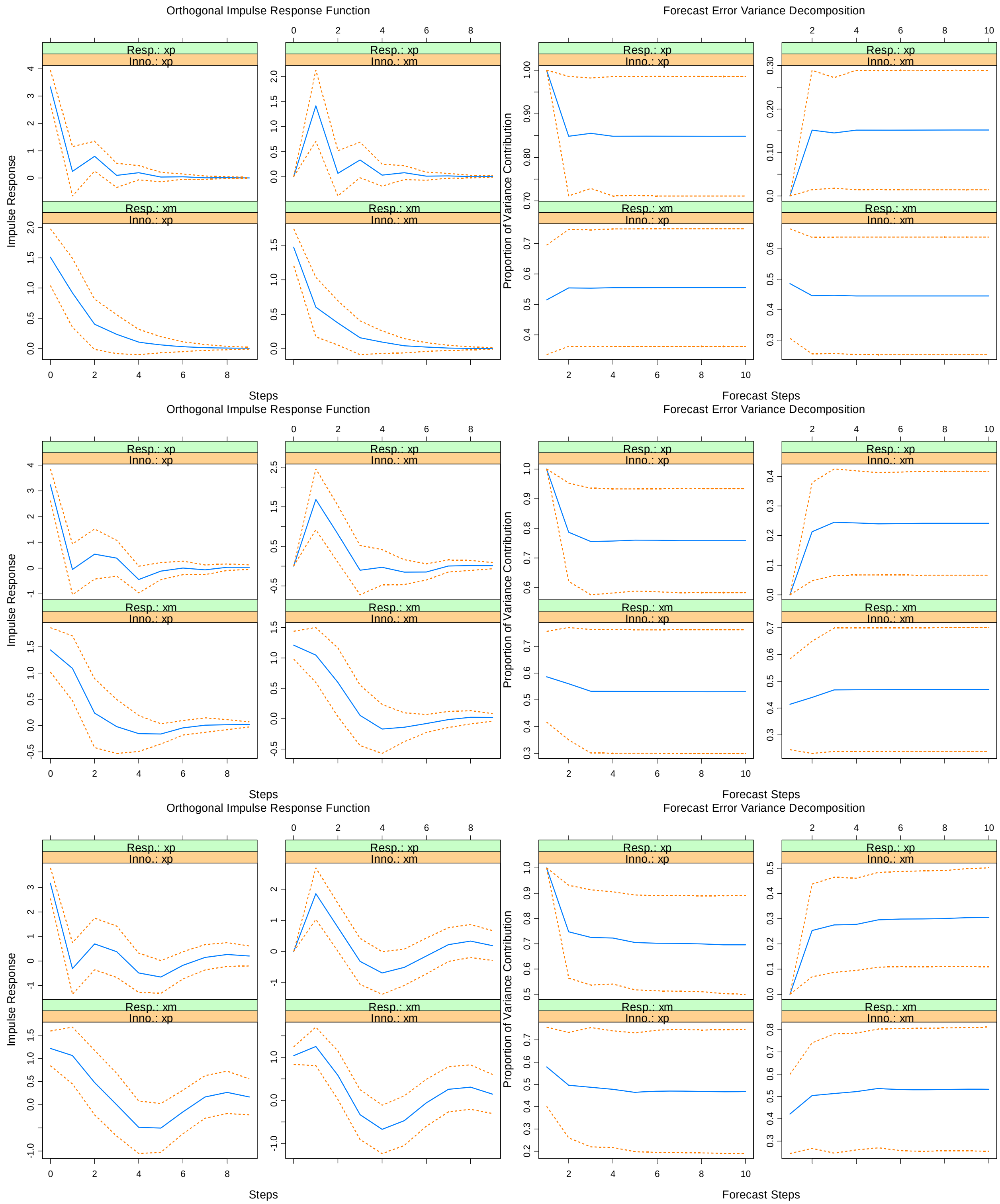

Figure A5: Observed Values (2005$/kg) and Predictions with 95% Confidence Bounds from the VAR Models (import prices, xm, are first; COAR prices, xp, are second in each pair of plots) Used in Chow Tests with (top to bottom) 1 Additional Observation in 2005, 1 Additional Observation in 2006, and 2 Additional Observations in 2005 and 2006, and (reproduced from above) 10-yr Forecasts 2007-2027 (index units 17-27) Conditional on Data from 1991-2006 (index units 1-16).