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Abstract

For a significant portion of the year there is a temporal lag in officially reported first-wholesale prices. This lag occurs because the prices are derived from the Commercial Operators Annual Report which is not available until after data processing and validation of the data in August of each year. The result is a data lag that grows to roughly a year and a half (e.g., prior to August 2014 the most recent available official prices were from 2012). To provide information on the current state of fisheries markets, now-casting is used to estimate 2014 first-wholesale prices from corresponding export prices which are available at a shorter time lag. Now-casting provided fairly accurate predictions and displayed rather modest prediction error with most of the confidence bounds within 5-10% of the price. In addition, time series models are used to project first-wholesale prices for 2015-2018. Resampling methods are used estimate a prediction density of potential future prices. Confidence bounds are calculated from the prediction density to give the probability that the prices will fall within a certain range. Prediction densities also provide information on the expected volatility of prices. As prices are projected past the current year the confidence bounds grow reflecting increasing uncertainty further out in the future. An empirical example to projecting the prices of pollock goods illustrates the methods. The full results of this research are published in the Status Report for the Groundfish Fisheries Off Alaska, 2014, provided to the North Pacific Fishery Management Council.

Contents

Introduction

The Stock Assessment and Fishery Evaluation Report for the Groundfish Fisheries of the Gulf of Alaska and Bering Sea/Aleutian Island Area: Economic Status of the Groundfish Fisheries Off Alaska, 2013 (Economic SAFE) provides first-wholesale prices for the groundfish products produced by U.S. North Pacific fisheries (Table 26, Fissel et al. (2014)). These prices are derived from production and revenue data collected from processors in the Commercial Operators Annual Report (COAR). Because of the COAR's submission deadline, data processing, and validation of the data from the report are not completed until July of the following year. Thus, at the time of the Economic SAFE's writing (October), the most recent pricing data available are for the previous year. For example, in October 2014 the most recent first-wholesale price data are for the calendar year 2013. Furthermore, because the report is annual, this remains the most recent data for much of the following year (2015 in the previous example). Price projections of first-wholesale products (Section 6, Fissel et al. (2014)) are published in the Economic SAFE to provide recent information on the state of the North Pacific fishing industry. Current prices (i.e., coresponding to the year the Economic SAFE's is written; 2014 in the previous example) are estimated ("now-cast") using corresponding export prices. Furthermore, first-wholesale prices are forecast out over the next 4 years (2015 to 2018 in the previous example). The projections give a probabilistic characterization of the range of future prices.

This report describes the methodology applied in projecting pound prices for Alaska fisheries first-wholesale products. The purpose of this document is to provide a concise description of the data and methods used to create price projections for first-wholesale North Pacific groundfish products. The description provided is intended to be sufficient for the reader to evaluate and reproduce the methods. A numbering modeling methods were used to provide accurate robust estimates. A complete treatment of the statistical theory and estimation strategies can be found by following the references.

The procedure used for constructing the price projections is summarized in the following section. Subsequent sections describes the first-wholesale and export data used for in the analysis,the estimation procedures of the time series models. This is follow by a discussion of the Monte Carlo simulation procedure that was used to obtain confidence bounds for pound prices and forecast combination.

The focus of this report is on modeling methods, however, an empirical illustration of the forecast methods have been provided in the final section of this report. The first-wholesale price projections for all products can be found in the Section 6 of the Economic SAFE (Fissel et al. (2014)) along with a brief description of the product markets for context and an informal evaluation of price projections based on news media reports.

Forecasting methods may be revised in the future which incorporate new data or improved methods.

Overview of First-wholesale Price Projection Methods

The methods for now-casting the current year's prices are distinctly different than the methods used to estimate future prices. Current year prices were now-cast using export prices which are available with a minimal time lag of up to 3 months. The regression relationship between export prices and first-wholesale prices was fairly strong for most products. Therefore, now-casts were made with fairly high precision, particularly in comparison to the projections of future prices. Only a small component of the future first-wholesale prices was forecastable, a feature that is common in price forecasts for commodities Chevallier and Ilepo (2013). Price projections were primarily made using models that estimate long-run returns and deviations from their long-run value. Estimates were made more robust by using a suite of canonical time series models to capture different aspects of the time series signal. The primary suite of models used were within the class of autoregressive moving average (ARMA) time series models (Hamilton 1994). Two exponential smoothing models were also used, however, these tended to contribute little to the price projections

(Hyndman and Athanasopoulos 2013). Changes in price return volatility over time were also modeled as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) processes. Confidence bounds for the estimated models were constructed using residual resampling methods. Simulations created a probabilistic distribution of potential returns that are consistent with historical deviations from the models. Price projections from the suite of models were then combined using weights that were determined by model fit. Prices were calculated from returns and statistics such as the mean and percentiles for confidence bounds were calculated from the forecast distribution

Data

The species and products for which price projections are made approximately correspond with the prices in Table 26 of the Economic SAFE (Fissel et al. (2014)). With the notable exception that estimates are made for all Alaska, and no distinction is made between at-sea and shoreside prices. For products where prices between the at-sea and shoreside sectors differ, then discrepancy is typically attributed to product quality or other production differences that are constant fairly constant over time. Because of this a forecast of the product price and be used to impute the sector specific product prices. Furthermore, export data which make no distinction between sectors, hence, aggregating over sectors aligns the product definition closer to the corresponding export product definition.

First-Wholesale Data

The first-wholesale product pound prices (hereafter prices) projected in this analysis were based on the published prices in Table 26 of the Economic SAFE (Fissel et al. (2014)).[1] The prices were based on the Commercial Operators Annual Reports, see footnotes on Table 26 of the Economic SAFE (Fissel et al. (2014)) for further source

[1]The data as published in Table 26 of the Economic SAFE is rounded however more detailed data can be obtained in csv format at: http://www.afsc.noaa.gov/REFM/Socioeconomics/SAFE/CSV_groundfish/table26_data.csv .

details. Price data extend from 1992 to 2013. Prices are stratified by three factors: species, product type, and inshore/off-shore sector. For this analysis a product is defined by the two characteristics: species and product type (e.g., pollock fillet). Sector prices were aggregated by taking an average over inshore and offshore prices weighted by product quantity.

Many of the products listed in Table 26 of the Economic SAFE are produced in relatively small quantities, to reduce the set of forecasts to set of products for which there is a significant market some products were aggregated. Specifically, any product whose average annual share of value for a given species was less than 10% was reclassified to the ”other products” product type. Exceptions to the product aggregation rule were: pollock fillets and pollock deep-skin fillets were not reclassified; most non-head and gut flatfish product types were reclassified as ”other products”; and ”rex sole other products” was only present in four non-contiguous years and was removed. Furthermore, all products from the species ”deep-water flatfish”, ”Kamchatka flounder”, ”other flatfish”, and ”other species” were removed from the analysis. These species were dropped because either the times series was not sufficiently long to make reasonable predictive estimates or the product definition was too ambiguous or highly aggregated to understand what product market was being estimated. The final list of products for which prices projections were made can be found on Table 1 along with abriged product names that are used in tables to conserve space.

Table 1.– First-wholesale North Pacific groundfish product and abbreviations.

Long product name	Product
pollock surimi	PLCK Suri
pollock roe	PLCK Roe
pollock fillet	PLCK Flt
pollock deep-skin fillet	PLCK DsFlt
pollock other products	PLCK Other
Pacific cod fillet	PCOD Flt
Pacific cod head and gut	PCOD H&G

Pacific cod other products	PCOD Other
sablefish head and gut	SABL H&G
yellowfin (BSAI) head and gut	YLWS H&G
rock sole (BSAI) head and gut with roe	RCKS H&GwR
rock sole (BSAI) head and gut	RCKS H&G
Greenland turbot (BSAI) head and gut	GLDT H&G
arrowtooth head and gut	ARTH H&G
flathead sole head and gut	FLTS H&G
rex sole (GOA) whole fish	REXS Whole
shallow-water flatfish (GOA) fillet	SHAL Flt
Atka mackerel head and gut	AMAK H&G
rockfish head and gut	RCKF H&G

Export Data

Data on U.S. exports of fisheries products were used to 'now-cast' recent first-wholesale prices (see the following section for nowcasting). Export data are collected on a monthly basis by the Foreign Trade Division of the U.S. Census Bureau and is typically available at a 2 to 3 month lag. The comparatively recent export data are used to predict the current annual price. The analysis used the monthly export quantities and revenues by product type, U.S. city of origin and export destination for January 1992 - August 2014.[2]. The product definitions for export data are different from the first-wholesale product definitions. The following is a list of the export product definitions considered in the analysis grouped by species or species complex:

- Pollock: "GROUNDFISH POLLOCK ALASKA FILLET FROZEN", "GROUNDFISH POLLOCK ALASKA ROE FROZEN", "GROUNDFISH POLLOCK ALASKA SURIMI", "GROUNDFISH POLLOCK NSPF MINCED FROZEN", "GROUNDFISH

[2]These data are available at:
http://www.st.nmfs.noaa.gov/commercial-fisheries/foreign-trade/applications/monthly-product-by-countryassociation

POLLOCK ALASKA FROZEN", "GROUNDFISH POLLOCK ALASKA MEAT FROZEN"

- Cod: "GROUNDFISH COD NSPF FILLET FROZEN", "GROUNDFISH COD NSPF FROZEN", "GROUNDFISH COD NSPF FRESH", "GROUNDFISH COD NSPF SALTED", "GROUNDFISH COD NSPF DRIED", "GROUNDFISH COD NSPF MINCED FROZEN", "GROUNDFISH COD NSPF MINCED FROZEN > 6.8KG"
- Sablefish: "SABLEFISH FROZEN", and "SABLEFISH FRESH"
- Flatfish: "FLATFISH SOLE YELLOWFIN FROZEN", "FLATFISH NSPF FILLET FROZEN", "FLATFISH NSPF FILLET FRESH", "FLATFISH SOLE ROCK FROZEN", "FLATFISH PLAICE FRESH", "FLATFISH PLAICE FROZEN", "FLATFISH NSPF FRESH", "FLATFISH NSPF FROZEN", "FLATFISH TURBOT GREENLAND FROZEN"
- Atka mackerel: "ATKA MACKEREL FROZEN"
- Rockfish: "GROUNDFISH OCEAN PERCH PACIFIC FROZEN"

Some export product definitions were combined into a single series by summing quantities and revenues. Data for the export product "GROUNDFISH COD NSPF MINCED FROZEN > 6.8KG" were aggregated with "GROUNDFISH COD NSPF MINCED FROZEN". Data defined as "FLATFISH NSPF FILLET FROZEN" were aggregated with "FLATFISH NSPF FROZEN". Data defined as "FLATFISH NSPF FILLET FRESH" were aggregated with "FLATFISH NSPF FRESH". Finally, data defined as "FLATFISH PLAICE FRESH" were aggregated with "FLATFISH PLAICE FROZEN". Furthermore, not all export product defined above were used. For example, the product "GROUNDFISH POLLOCK NSPF MINCED FROZEN" was dropped because data were only present in 1991. In general, any time series containing less than 10 years was not used in the analysis. Similarly, the time series for export products "GROUNDFISH POLLOCK ALASKA FROZEN" and "GROUNDFISH POLLOCK ALASKA MEAT FROZEN"began in 2010 and 2012, respectively, and were not used.

A few of the export time series has a gap of few years in the middle of the time series and where this occurred missing years were imputed at the average product price returns. Alternative imputation methods were explored and yielded similar results. Export data were further constrained to exports originating from Washington and/or Alaska. An analysis of alternative point-of-origin constraints indicated that in-sample predictions of first-wholesale prices improved when export data were restricted to these states.

The monthly export quantities and revenues were aggregated by summing over the months within a year. If the months of the current year being predicted (e.g., 2014) did not yet span the full year, then only the months with export data available in the 'current' year were summed in each year. For example, if in 2014 export data were only available through September, then export prices for all years were calculated using only data through September in every year. This is because the objective of analysis is predicting current first-wholesale prices using (potentially) partially available export data. Quantities in the export data are denoted in kilos which can be converted to pounds using a factor of 2.20462 (2.20462*kilos≈pounds). Export prices were calculated as dividing export revenues (denoted in U.S.$) by quantities.[3]

Modeling and Estimation

Price Stationarity and Return Calculations

Price projections were estimated on annual returns rather than prices. Financial time series analysis is typically conducted on asset returns. The primary reason is that statistical tests on raw asset prices generally indicate the presence of a stochastic trend known as a unit root. Unless accounted for, stochastic trends can create statistical difficulties such as falsely identified (spurious) relationships between prices which are actually unrelated (see Chapter 18, Hamilton (1994) for details on unit roots).[4] The presence of unit roots were confirmed in first-wholesale prices data using the

[3]Subsequent regression analysis would not be affected if prices were left as dollars per kilo because the conversion factor is constant.

[4]See Chapter 5, Chevallier and Ilepo (2013) for a general discussion of unit roots in commodity prices.

Augmented Dick-Fuller and Philips-Perron unit root tests. Because unit roots are so ubiquitous in financial time series the results of the unit root tests are not presented here. Unit roots can be filtered by calculating returns. Returns were calculated as $r_t = ln(p_t) - ln(p_{t-1})$, where r_t and p_t represent returns and prices, respectively, at time t and $ln()$ is the natural logarithm. Unit root tests conducted on the return series rejected the presence of a unit root indicating that the time series were stationary and suitable for canonical time series methods.

Methods for Now-casting First-wholesale Returns Using Export Data

Now-casting is the prediction of a variable for a time period that has partially or completely occurred, but for which data are not yet available. Now-casting is widely used by agencies for the timely reporting critical economic data for which there is some reporting lag in the underlying data. For example, now-casting is used by the Bureau of Economic Analysis to estimate recent quarters of U.S. Gross Domestic Product. Subsequent revisions to GDP are the largely the result of new data becoming available (Banbura et al. 2013).

Now-casting is used to estimate average annual first-wholesale returns for groundfish products in 2014 which, at the time the Economic SAFE is written, had only partially occurred. Predictions were made using U.S. export returns for groundfish products for which data are available with a minimal time lag. The relationship between export returns and first-wholesale returns is modeled through linear regression, which when used in a now-casting framework is sometimes referred to as a "bridge" regression.

Analysis of the time series profile of first-wholesale production quantities and export quantities for a given species (or species and product type where product type definition roughly matched) generally showed a distinct break in the relationship in the year 1998. From 1998 on first-wholesale production and exports were roughly proportional while earlier years export quantities tended to be significantly smaller and the relationship was more erratic. Furthermore, inclusion of pre-1998 data generally reduced predictability. Because of this, now-cast models were fit and prediction of recent returns were made based on post-1997 data.

For each product that was now-cast, all export variables matching the first-wholesale species, or species complex, were tested. These matches correspond with the groupings in the itemized list in the previous section titled 'Export Data'.[5] Variable selection was based on the Akaike and Bayesian Information Criterions. Model residuals were tested for heteroskedasticity and autocorrelation. Residual autocorrelation was tested using the Breuch-Godfrey test up to 3 lags and results indicated that residuals were independent. However, many models exhibited at least some heteroskedasticity both visually and as determined by a Breusch-Pagan test. Furthermore, visual analysis of series and model residual indicated the occasional presence of outliers. To mitigate the potential leverage from heteroskedasticity and outliers, models were fit using the robust linear estimation method of iterated re-weighted least squares. For the product 'Atka mackerel head and gut' iterated re-weighted least squares failed to converge and models were estimated by ordinary least squares. Table 2 presents the regression model specifications.

Specific parameter estimates are not provided in this report. The unadjusted R-squared has been calculated to provide some indication of how well the export models perform relative to the mean. However, R-squared was not used in model selection and the properties of R-squared in a robust linear estimation and Ordinary Least Squares (OLS) frameworks may not coincide. Thus, the R-squared statistic should be viewed only as a statistic comparing the fitted and the mean deviations and not as a measure of goodness-of-fit.

Now-casted returns were used in the subsequent price projection models. The now-casted price is calculated by inverting the return calculation with a log-normal adjustment to account for the estimation randomness:

$$p_{i,2013} * exp(\check{r}_{i,2014} + \check{\sigma}^2_{i,2014}/2) = \check{p}_{i,2014}, \quad (1)$$

[5]A limited number of cross-species variables were attempted but they weren't found to increase predictability significantly. Thus cross-species variables were excluded from the models based on these trials, the limited observations and the large number of possible combinations if all variables were tested.

Table 2.– Now-cast model specifications.

Product	Variables	R-Squared
PLCK Suri	SURIMI, DV 08-09, DV PRE-2K	0.54
PLCK Roe	ROE, DV 07-10	0.64
PLCK Flt	FILLET, DV PRE-01	0.23
PLCK DsFlt	FILLET, DV PRE-01	0.01
PLCK Other	FILLET	0.02
PCOD Flt	FILLET, NSPF FROZEN, DRIED, DV 03	0.60
PCOD H&G	NSPF FROZEN, DRIED, FRESH	0.47
PCOD Other	NSPF FROZEN, FRESH, SALTED, MINCED, DV PRE-01	0.65
SABL H&G	FROZEN, FRESH	0.33
YLWS H&G	SOLE YELLOWFIN, (SOLE YELLOWFIN)*(DV PRE-07), PLAICE	0.14
RCKS H&GwR	SOLE ROCK, PLAICE, NSPF FRESH	0.32
RCKS H&G	SOLE ROCK, SOLE YELLOWFIN, PLAICE	0.42
GLDT H&G	TURBOT GREENLAND	0.21
ARTH H&G	TURBOT GREENLAND, NSPF FROZEN, SOLE ROCK	0.10
FLTS H&G	TURBOT GREENLAND, SOLE ROCK, DV 06, SOLE YELLOWFIN, NSPF FROZEN	0.36
REXS Whole	NSPF FROZEN, PLAICE, DV 05&11	0.69
SHAL Flt	NSPF FROZEN, SOLE ROCK, NSPF FRESH, DV 04-05	0.76
AMAK H&G	FROZEN	0.12
RCKF H&G	FROZEN	0.00

'DV YY' is a dummy variable for the indicated years.

where $exp(x) = e^x$ is the exponential function, $\check{r}_{i,t}$ ($\check{p}_{i,t}$) is the now-casted return (price) of product i and $\check{\sigma}^2_{i,t}$ is the prediction error from the regression.

Methods for Projecting First-wholesale Returns for Future Years

Time series forecasting models are not generally a structural model of a data generating process. Rather, forecasting models construct a parsimonious parametric structure that captures features of the series' evolution over time (e.g., if I observe y_t today can I expect to observe $y_{t+1} = \rho y_t$ tomorrow on average?). Different models can capture different features of the dynamics of time series'. Furthermore, the forecast performance of these different models can be improved by combining the forecasts from the individual models (Timmermann 2006).

The forecast procedures used here follow this approach of forecasting with multiple parsimonious models then combining the forecasts. Forecasts were made using two classes of models:1) ARMA models and 2) exponential smoothing models (ETS). Models were combined using weights determined by their forecast performance as measured by a small-sample-adjusted Akaike Information Criterion (AICc) (Burnham and Anderson 2002). The following sections describe the classes of forecast models.

ARMA Time Series Models

The autoregressive moving-average (ARMA) model is the work-horse of time series analysis. The ARMA models captures linear dependence between future and earlier observations of both the observed returns and the error process. The ARMA(p, q) model of returns, r_t, posits the following dynamic relationship:

$$r_{t+1} = \alpha + \sum_{i=1}^{p} \rho_i r_{t+1-i} + \sum_{j=1}^{q} \phi_j \varepsilon_{t+1-j} + \varepsilon_{t+1}, \tag{2}$$

where p is the number of autoregressive (AR) terms and q is the number of moving-average (MA) terms. The residuals $\{\varepsilon_t\}$ were assumed to be a white-noise process with mean of zero, a finite variance, and is uncorrelated with all other realizations. The parameters of the autoregressive component, ρ_i, capture the dependence between r_{t+1} and previous observed returns, r_{t+1-i}, $i > 1$. The parameters of the moving-average component, ϕ_j capture the dependence between the return r_{t+1} and previous errors, ε_{t-1}. Trends in the context of ARMA models were considered by including functions of time directly in Equation 2 (e.g., $\gamma_1 t + \gamma_2 t^2....$). Time trends were not supported empirically and were not included in any of the final ARMA models. All ARMA models included a constant.

Parameter estimation of ARMA(p, q) models can be carried out using the Kalman filter procedure. The Kalman filter is a recursive procedure to calculate maximum likelihood estimates of all of the ARMA model's parameters (see Chapter 13, Hamilton (1994)). For a given p and q, estimated parameters, $\hat{\rho}_i$ $i = 0, ..., p$ and $\hat{\phi}_j$ $j = 0, ..., q$, and residuals $\hat{\varepsilon}_s$ $s = 1, ..., t$ forecasts of r_{t+1} were made from Equation 2 as

$$\hat{r}_{t+1} = \hat{\alpha} + \sum_{i=0}^{p} \hat{\rho}_i r_{t-i} + \sum_{j=0}^{q} \hat{\phi}_j \hat{\varepsilon}_{t-j}. \tag{3}$$

Return forecasts ARMA(p, q) models were estimated for orders $0 \leq p \leq 3$, $0 \leq q \leq 3$. Because of the limited number of observations and to preserve degrees of freedom in estimation, the set of ARMA models were further restricted to $p + q \leq 3$. The AICc are well defined model selection statistics for ARMA models. Table 9 presents the estimated model model coefficients and AICc statistics.

Exponential Smoothing Time Series Models

The exponential smoothing (ETS) approach models a dynamic process as a weighted average of past observations with weights that decay exponentially. The discussion of these models closely follows Hyndman and Athanasopoulos (2013). ETS models decompose time series into a state space where the decay and drift are modeled as explicit but unobserved states. Forecasts were made using a simple exponential smoothing model and an exponential smoothing trend model.

The simple exponential smoothing model has a single parameter, α which controls the decay of the weights from the most recent observation. It posits the following model written in state-space form:

$$r_{t+1} = l_t + \varepsilon_{t+1} \tag{4}$$

$$l_{t+1} = l_t + \alpha\varepsilon_{t+1}, \tag{5}$$

where $0 < \alpha < 1$ and ε_{t+1} ˜ iid $N(0, \sigma^2)$. The latent state l_t is referred to as the level. Recursive substitution of equations above expresses r_{t+1} in terms of previous values:

$$r_{t+1} = \sum_{i=0}^{t-1} \alpha(1 - \alpha)^i r_{t-i} + (1 - \alpha)^t l_0 + \varepsilon_{t+1}, \tag{6}$$

showing it is exponential smoother from initial state "l_0" where larger values of α give comparatively greater weight to recent observations. The forecast of r_{t+1} can be expressed as a weighted average of the previous observation and its expected value, $E_t(r_{t+1}) = \alpha r_t + (1-\alpha)E_{t-1}(r_t)$.

The exponential smoothing trend model augments Equation 4 with a trend positing the following time series structure:

$$r_{t+1} = l_t + b_t + \varepsilon_{t+1} \tag{7}$$

$$l_{t+1} = l_t + b_t + \alpha\varepsilon_{t+1} \tag{8}$$

$$b_{t+1} = b_t + \alpha\beta\varepsilon_{t+1}, \tag{9}$$

where $0 < \alpha < 1$ and β is a smoothing parameter. Time series with smaller values of β have a trend component with less variation on average, thus resulting in a smoother trend and observations. This model reduces to the previous case of simple exponential smoothing (Equation 4) when $\beta = 0$ and $b_0 = 0$. Equation 7 can be rewritten as

$$r_{t+1} = \sum_{i=0}^{t-1} \alpha(1-\alpha)^i r_{t-i} + (1-\alpha)^i b_{t-i} + (1-\alpha)^t(l_0 + b_0) + \varepsilon_{t+1}. \tag{10}$$

Smaller values of α again give greater weight to more recent observations. The addition of the trend b_t incorporates the slope of r_t as a predictor (Hyndman and Athanasopoulos 2013). The exponential state space trend is different from the time deterministic trends in ARMA models where trend refers to a variable that is an explicit function of time t.

The forecast of the trend exponential smoothing model can be expressed as the weighted average of the previous observation and its expected value plus the trend: $E_t(r_{t+1}) = \alpha r_t + (1-\alpha)E_{t-1}(r_t) + b_t$.

Due to their recursive structure, exponential smoothing models must be estimated using maximum likelihood. The AICc are well defined model selection statistics for exponential smoothing models. Table 10 lists the estimated model coefficients and AICc statistics.

Volatility Estimation

Volatility characterizes the spread of the distribution of the random innovations to a time series. Volatility can be time-varying, which if neglected can distort the spread of the forecast distribution by over- or underestimation of the variance. One particular time-varying feature frequently displayed is the tendency for periods of high (low) volatility to be followed by another period of high (low) volatility which is known a volatility persistence. Volatility persistence is a typical feature of commodity prices (Chevallier and Ilepo 2013) and is one which is also displayed by some of the returns of first-wholesale fisheries products.

Neglecting to account for time varying volatility can result in forecasts with too much or too little volatility in the forecast distribution depending on the current state of volatility. A standard method for accounting for volatility persistence is to estimate a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Specifically, this analysis estimates a GARCH(1,1) model for the volatility. The GARCH(1,1) model can be written as

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \sigma_{t-1}^2 + u_t. \tag{11}$$

Similar to the ARMA(p,q) model the (1,1) in GARCH(1,1) refers to the number of lagged squared residual, ε^2, and squared volatility, σ^2, terms used in the model. Note that the true volatility σ is unobserved. The model is estimated using $\hat{\varepsilon}_t$ from the estimated ARMA and ETS models. Specifically, for each species-product and each model estimated The GARCH(1,1) model is fit to each of the estimated models presented above.

The GARCH model implies a long-run equilibrium volatility. The long-run volatility of the GARCH(1,1) model can be computed directly from the estimated coefficients as

$$\sigma_{long-run}^2 = \frac{\gamma_0}{1 - \gamma_1 - \gamma_2}. \tag{12}$$

GARCH models were estimated using maximum likelihood and convergence of the models is know to be difficult. Convergence is further complicated by the limited number of observations. Alternative search algorithms were used, data were rescaled, and different initial conditions were attempted to facilitate convergence. When convergence failed the canonical constant volatility of the ARMA model was used. If multiple convergence points were found after trying these alternatives then the model that minimized the Bayes Information Criterion (BIC) was chosen. Finally, the implied estimated long-run volatility (Eq.12) was examined relative to the distribution of the squared residuals and if the long-run volatility was above the 95th quantile or below the 5th quantile then it was treated as if the model had converged at a bad point and again the canonical constant volatility of the ARMA model was used for the price projections.[6]

In addition to producing volatility forecasts, the fitted GARCH volatilities were used to normalize residuals from the fitted ARMA models prior to resampling in the subsequent simulations. GARCH normalized residuals were calculated as follows: let $\hat{\varepsilon}_{m,i,t}$ be the residual and $\hat{\sigma}_{m,i,t}$ the estimated volatility for product i (e.g., pollock surimi) from model $m \in M$ where $M = \{1, 2, \ldots\}$ indexes the forecasting models (e.g., ARMA(1,1)). The residual is normalized by the estimated volatility (Equation 11), $\ddot{\varepsilon}_{m,i,t} = \frac{\hat{\varepsilon}_{m,i,t}}{\hat{\sigma}_{m,i,t}}$.

Wholesale Price Simulations

The objective of simulating the prices rather than relying on standard distribution theory is to produce accurate prediction densities for calculating confidence bounds. The residuals from the fisheries returns have features that aren't consistent with a normally distributed error process. Abnormally distributed errors are characteristic of financial time series (Chevallier and Ilepo 2013). Large errors of three standard deviations or more are too common. Roughly 20% of the normalized residual series

[6]For some of the estimated models the coefficient on lagged volatility γ_2 was significant and large. However results varied across products significantly. Some parameters were sufficiently large to suggest an IGARCH model however these were not considered, though they may be tested in the future.

have an excess kurtosis observed greater than one and the maximum excess kurtosis is approximately 5.5. If confidence bounds were based on the canonical assumption of normally distributed errors they would be too small and fail to contain future realized returns with the correct probability.

Accurate confidence bounds were produced using a Monte Carlo simulation of the time series models that randomly sample hypothetical residuals from an empirical distribution and treats them as realized errors which are propagated through the estimated time series models. The empirical distributions were constructed from the residuals of the corresponding estimated models normalize by the volatilities. Because the time series were relatively short the empirical distribution of residuals for a single time series is not sufficiently rich to characterize the true error distribution and may be subject to small sample bias from extreme events. The empirical distributions were made more robust by pooling normalized residuals across products for a given model type. The procedures for residual pooling and return simulation are described in the following sections.

Residual Pooling

For each model and product the 22 residuals across time from the regression alone were not rich enough to characterize an empirical distribution. Especially, one potentially subject to extreme events. To see this, consider the case where an 'abnormally' large deviation that occurs with probability 0.01 and was observed in one of the sample years. However, with only 22 under the empirical distribution this 'abnormal' event has a $\frac{1}{22} = 0.045$ chance of being draw, thus over representing the 'abnormal' event. Residuals pooling can alleviate this problem by using combining the residuals from the other product regressions into a single empirical distribution for a given model, $\{\ddot{\varepsilon}_{m,i,t}\}|_{M=m}$. A sufficient condition validating the pooling is that the normalized residuals are identically distributed, $F(\ddot{\varepsilon}_{m,i,t}) = F(\ddot{\varepsilon}_{m,j,s})$ for all products i, j, times s, t and a fixed model m. Equality of distributions across products was supported by Kolmogorov-Smirnov tests.[7] Table 3 presents the proportion of test statistics that reject the null of equal distributions at the 5% significance level is slightly 5% supporting the assumption that the distributions were equal.

Table 3.– Proportion of tests rejecting the null of equal distributions at 5% significance.

ARMA(0,0)	ARMA(0,1)	ARMA(0,2)	ARMA(0,3)	ARMA(1,0)	ARMA(1,1)
0.039	0.033	0.044	0.035	0.032	0.036
ARMA(1,2)	ARMA(2,0)	ARMA(2,1)	ARMA(3,0)	ETS(AAN)	ETS(ANN)
0.043	0.040	0.046	0.038	0.030	0.040

Return Simulation

Return were simulated for the years 2015-2018. Returns were simulated by randomly sampling from the pooled residual distribution and plugging these samples into the fitted models. The pooled residual distributions were ordered and indexed prior to random sampling so that residuals for the same product and time were used when forecasts were subsequently combined. Thus, for a randomly sampled index ι and models m and m', $\ddot{\varepsilon}_{m,i,t}(\iota)$ and $\ddot{\varepsilon}_{m',i,t}(\iota)$ were sampled normalized residual from the same product i and same time t but different models. The index ι is a randomly sampled number from $1, 2, ..., V$ where V is the number of products times the number of observations. Let $\iota(t)$ be the randomly drawn index (e.g., $\iota(2015)$) so that $\ddot{\varepsilon}_m(\iota(t))$ is a randomly sampled normalized residual that will be used to simulate year t. The volatility corrected sampled residual for product i, and model m is $\varepsilon^*_{m,i,t} = \ddot{\varepsilon}_m(\iota(t)) * \sigma_{m,i,t}$, where $\sigma_{m,i,t}$ is the fitted GARCH(1,1) volatility. Thus, $\hat{\varepsilon}_{m,i,t}$ and $\varepsilon^*_{m,i,t}$ are the in-sample residual and randomly sampled residuals; $r_{i,t}$ and $\hat{r}_{m,i,t}$ are the observed and fitted (or simulated) returns and $\hat{f}_{m,i}$ is the fitted model. Informally, residual pooling is justified under the assumtion that a deviation (suitably normalized) that occurred in one product market, could have actually occurred in any other product market.

The following algorithm was used to simulate returns.

[7] Alternative distribution tests such as the and Anderson-Darling K-sample tests were also implemented with similar results.

1. Randomly draw four indices for the simulated years: $\iota(2015)$, $\iota(2016)$, $\iota(2017)$ and $\iota(2018)$.
2. From the model m pooled residuals and the randomly drawn indices construct the volatility corrected residuals (as described above): $\varepsilon^*_{m,i,2015}$, $\varepsilon^*_{m,i,2016}$, $\varepsilon^*_{m,i,2017}$,, $\varepsilon^*_{m,i,2018}$.
3. Iteratively calculate the following equations for the fitted model m and product i:

$$
\begin{aligned}
\hat{r}_{m,i,2015} &= \hat{f_{m,i}}(r_{i,2014}, r_{i,2013}, ..., \varepsilon_{m,i,2014}, \varepsilon_{m,i,2013}, ...) + \varepsilon^*_{m,i,2015} && (13)\\
\hat{r}_{m,i,2016} &= \hat{f_{m,i}}(\hat{r}_{m,i,2015}, r_{i,2014}, ..., \varepsilon^*_{m,i,2015}, \varepsilon_{m,i,2014}, ...) + \varepsilon^*_{m,i,2016} && (14)\\
\hat{r}_{m,i,2017} &= \hat{f_{m,i}}(\hat{r}_{m,i,2016}, \hat{r}_{m,i,2015}, ..., \varepsilon^*_{m,i,2016}, \varepsilon^*_{m,i,2015}, ...) + \varepsilon^*_{m,i,2017} && (15)\\
\hat{r}_{m,i,2018} &= \hat{f_{m,i}}(\hat{r}_{m,i,2017}, \hat{r}_{m,i,2016}, ..., \varepsilon^*_{m,i,2017}, \varepsilon^*_{m,i,2016}, ...) + \varepsilon^*_{m,i,2018} && (16)
\end{aligned}
$$

4. Repeat steps 2 and 3 for all models $m \in M$.
5. Repeat steps 1-4 10,000 times.
6. Repeat steps 1-5 for each product $i \in I$.

Forecast Combination

Forecast combination is a method for aggregating multiple forecasts from a set of models, typically using an average or weighted average. Forecast combination frequently improves forecast ability by permitting simultaneous use of many models that capture different features of the dynamic process.

The AICc goodness-of-fit statistics of the ARMA and ETS models that were used here generally fall within a small range as displayed by the clustering in Figure 1. This indicates that no single model significantly outperforms other models.[8] The limited number of observations prevent the use of a hold-out sample to construct a more robust forecast criterion for out-of-sample goodness-of-fit (e.g., through cross

[8]Smaller AICc values indicate better model fit.

validation). Criterion, such as AICc, that account for model complexity are preferred to other in-sample measure of fit such as Mean Squared Error (Burnham and Anderson 2002).

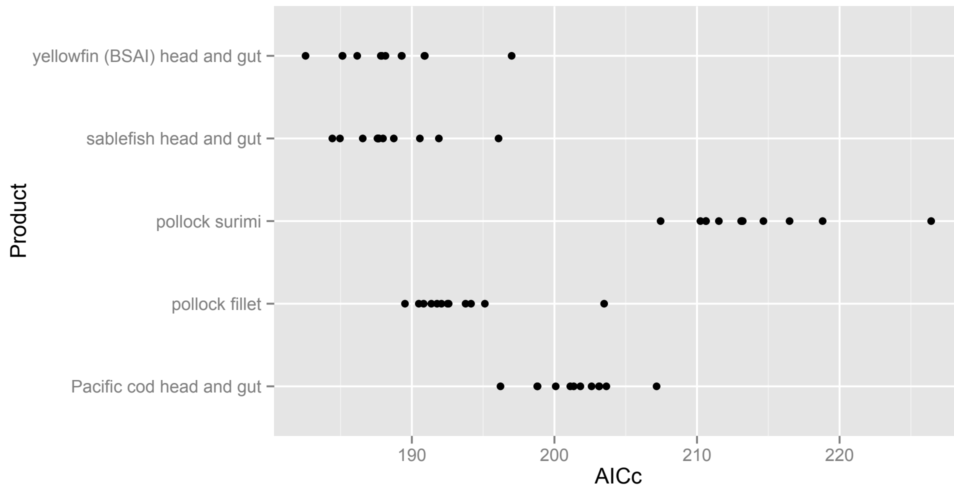

Figure 1.– AICc statistics of key products.

To account for the relative goodness-of-fit of the competing models, AICc weights were used for the weighted average of the forecast models. Weights were calculated by comparing the AICc statistic of each model relative the minimum AICc statistic (i.e., the model with the best fit):

$$\omega_{m,i} = \frac{exp(-0.5 * (AIC_{m,i} - AIC_{min,i}))}{\sum_{k=1}^{M} exp(-0.5 * (AIC_{k,i} - AIC_{min,i}))}, \tag{17}$$

where $AIC_{m,i}$ is the AICc statistic of model m and product i; $AIC_{min} = min_m(AIC_{m,i})$.

Empirical forecasting research has found that forecast combination using a simple average ($\frac{1}{N}$ forecast combination) generally performs very well and sometimes performs better than weighted averages based on forecast ability or model fit (Timmermann 2006). In practice, this empirical result is accounted for by shrinking the model-fit weights (Eq. 17) towards the simple average $\frac{1}{N}$. A shrinkage factor of 0.5 is used and the limited number of observations hinder the tuning of an optimal shrinkage factor. Trials with alternative factors local to 0.5 yielded qualitatively similar forecast results,

$$\omega^*_{m,i} = 0.5 * \omega_{m,i} + 0.5 * {}^{1}\!/\!{}_{N}. \tag{18}$$

The ARMA(0,0) (random walk), MA(1), MA(2), and AR(1) models tend to fit best and account for 51% of the weight on average (Table 4).[9]

Each of the 10,000 return projections were combined using a weighted average of the projected returns (Eq. 13) with the model weights in Equation 18,

$$\hat{r}^*_{i,t} = \sum_{m=1}^{M} \omega^*_{m,i} * \hat{r}_{m,i,t}. \tag{19}$$

[9] ARMA(0,1)=MA(1), ARMA(0,2)=MA(2) and ARMA(1,0)=AR(1)

Table 4.– Forecast combinations model weights.

Product	ARMA.0.0.	ARMA.1.0.	ARMA.2.0.	ARMA.3.0.	ARMA.0.1.	ARMA.1.1.	ARMA.2.1.	ARMA.0.2.	ARMA.1.2.	ARMA.0.3.	ETS.AAN.	ETS.ANN.
PLCK Suri	0.056	0.106	0.057	0.048	0.075	0.056	0.044	0.292	0.090	0.091	0.042	0.043
PLCK Roe	0.045	0.043	0.342	0.105	0.044	0.043	0.106	0.084	0.051	0.054	0.042	0.042
PLCK Flt	0.177	0.079	0.121	0.090	0.085	0.070	0.068	0.108	0.056	0.054	0.042	0.050
PLCK DsFlt	0.290	0.112	0.057	0.044	0.111	0.057	0.044	0.057	0.044	0.047	0.044	0.093
PLCK Other	0.043	0.056	0.053	0.044	0.341	0.108	0.054	0.108	0.054	0.054	0.042	0.042
PCOD Flt	0.201	0.088	0.065	0.046	0.096	0.110	0.058	0.124	0.059	0.059	0.042	0.051
PCOD H&G	0.290	0.108	0.060	0.047	0.109	0.076	0.049	0.062	0.049	0.051	0.043	0.057
PCOD Other	0.141	0.068	0.138	0.059	0.076	0.067	0.061	0.169	0.065	0.065	0.042	0.048
SABL H&G	0.164	0.073	0.059	0.045	0.074	0.094	0.066	0.193	0.070	0.070	0.042	0.049
YLWS H&G	0.294	0.109	0.058	0.045	0.110	0.081	0.050	0.059	0.050	0.045	0.042	0.057
RCKS H&GwR	0.105	0.063	0.049	0.071	0.131	0.133	0.073	0.153	0.063	0.071	0.042	0.046
RCKS H&G	0.063	0.189	0.074	0.051	0.200	0.077	0.061	0.084	0.050	0.066	0.042	0.043
GLDT H&G	0.057	0.052	0.054	0.045	0.242	0.118	0.060	0.137	0.087	0.064	0.042	0.043
ARTH H&G	0.042	0.045	0.057	0.048	0.314	0.114	0.060	0.121	0.058	0.059	0.042	0.042
FLTS H&G	0.202	0.117	0.062	0.058	0.119	0.059	0.104	0.061	0.050	0.074	0.042	0.052
REXS Whole	0.194	0.083	0.074	0.053	0.088	0.057	0.076	0.141	0.063	0.068	0.043	0.059
SHAL Flt	0.177	0.111	0.076	0.048	0.144	0.107	0.048	0.090	0.054	0.053	0.042	0.050
AMAK H&G	0.283	0.109	0.068	0.056	0.113	0.062	0.048	0.065	0.046	0.050	0.044	0.057
RCKF H&G	0.230	0.099	0.079	0.057	0.107	0.082	0.053	0.092	0.055	0.050	0.042	0.053

Calculating Price Projection Confidence Bounds

Prices were calculated by inverting the calculation made for returns (see the section titled Price Stationarity and Return Calculations). Simulated future returns were used to constructed simulated prices by starting from the calculated now-cast price $\check{p}_{i,2014}$ and using predicted returns to calculate the $t+1$ price: $p_{i,t} * exp(\hat{r}_{i,t+1}) = \hat{p}_{i,t+1}$. Iterating this calculation forward produces prices for the years 2015 to 2018. Prices were calculated for each fo the 10,000 simulated combined forecasts. The result is a distribution of simulated projected prices.

Confidence bounds for prices were obtained by calculating quantiles of the forecast distributions. Calculations were made for the 5%, 10%, 20%, 30%, 50%, 70%, 80%, 90%, and 95% quantiles. Intervals can be obtained by using the corresponding confidence bounds. For example, a 90% confidence interval can be constructed from the 5% and 95% confidence bounds.

Empirical Illustration of Price Projection Methods to Pollock Surimi, Fillets and Roe

The following empirical example illustrates the results of applying the previously described methods to pollock surimi, pollock fillets (excluding deep-skin fillets), and pollock roe. With a catch of 1.37 million metric tons (t) in 2013 the North Pacific pollock fishery is the largest fishery by volume in the United States. The first-wholesale revenue totaled $1.33 billion in 2013 making it the highest value groundfish fishery in Alaska (Fissel et al. 2014). Surimi, fillets and roe are primary product types made from pollock and accounted for 28.4%, 28.1% and 8.7% of the total first-wholesale value from pollock in 2013. Table 5 summarizes the realized first-wholesale prices from 2011 to 2013 and price projections for 2014 to 2016. The summary data provided for the years 2014 to 2016 are the expected price (mean) and 90% confidence bounds.

Tables 6, 7, and 8 provide a finer breakdown of the prediction densities. Confidence bounds give the probability that the price will fall within the bound. Thus, for the 5% bound, 5% of the simulated prices were less than the given value. Similarly, for

Table 5.– Pollock surimi, fillet and roe price projection summary.

Product	Stat.	2011	2012	2013	2014	2015	2016
PLCK Suri	mean	1.281	1.422	1.005	1.044	0.98	0.998
PLCK Suri	CI 90				[1.03,1.06]	[0.89,1.08]	[0.9,1.12]
PLCK Flt	mean	1.5	1.469	1.354	1.351	1.409	1.418
PLCK Flt	CI 90				[1.33,1.37]	[1.31,1.52]	[1.29,1.56]
PLCK Roe	mean	3.595	4.226	3.253	2.675	2.901	3.109
PLCK Roe	CI 90				[2.63,2.72]	[2.67,3.17]	[2.71,3.58]

the 95% bound, 95% of the simulated prices were less (and 5% were greater). Hence, the region between the 5% and 95% bounds can be interpreted as the 90% confidence bound. Smaller confidence bounds indicate less uncertainty in the projections. Figures 2, 3, and 4 display the mean predicted price and 90%, 80%, 60% and 40% confidence intervals corresponding to the confidence bounds in the tables.

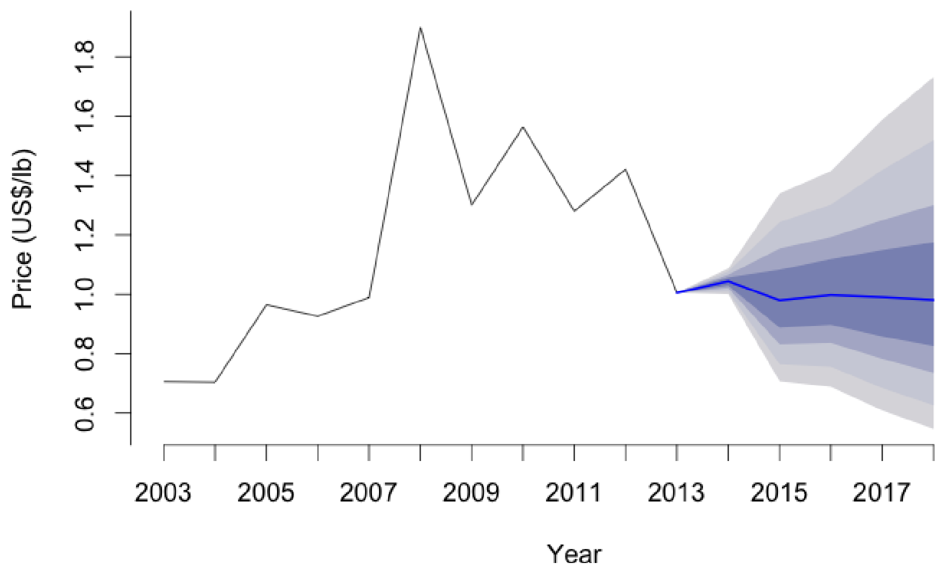

Figure 2.– Pollock surimi price projections and confidence bounds.

Table 6.– Projected mean, probability bounds of first-wholesale pollock surimi prices.

	Lower						Upper			
	5%	10%	20%	30%	Mean	Median	70%	80%	90%	95%
2014	1.00	1.01	1.02	1.03	1.04	1.04	1.06	1.07	1.08	1.09
2015	0.71	0.76	0.83	0.89	0.98	0.98	1.08	1.15	1.24	1.34
2016	0.69	0.76	0.84	0.90	1.00	1.01	1.12	1.19	1.30	1.42
2017	0.61	0.68	0.78	0.86	0.99	0.99	1.15	1.25	1.42	1.59
2018	0.55	0.63	0.74	0.83	0.98	0.99	1.18	1.30	1.52	1.73

At the 'Lower' and 'Upper' bounds x% of the simulated prices were less. The confidence bounds are the regions between the 'Upper' and 'Lower' bounds.

Pollock surimi return volatility projections

Hist. Avg.	2015	2016	2017	2018	Long-run
20.61	20.60	20.60	20.60	20.60	20.60

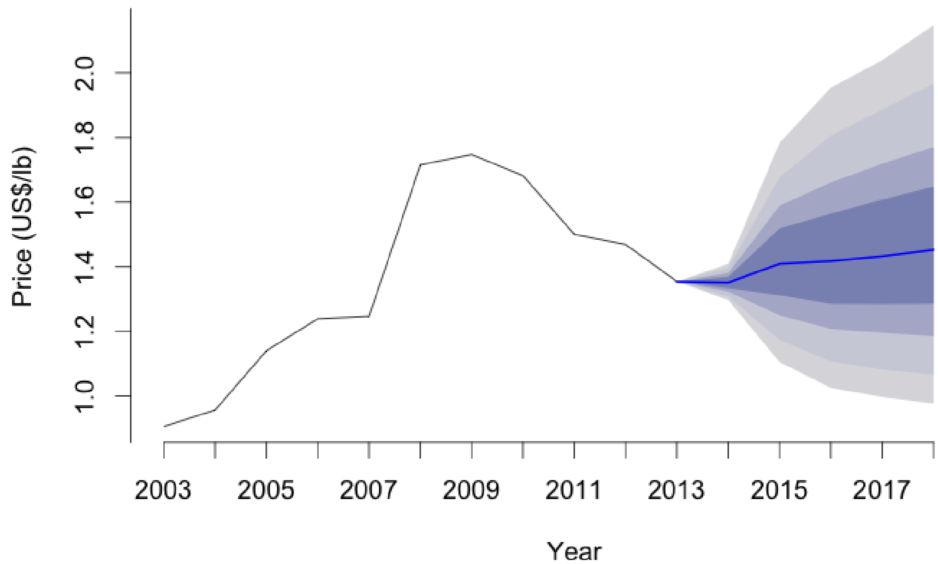

Figure 3.– Pollock fillet price projections and confidence bounds.

Table 7.– Projected mean, probability bounds of first-wholesale pollock fillet prices.

	Lower						Upper			
	5%	10%	20%	30%	Mean	Median	70%	80%	90%	95%
2014	1.30	1.31	1.32	1.33	1.35	1.35	1.37	1.38	1.40	1.41
2015	1.11	1.17	1.25	1.31	1.41	1.42	1.52	1.59	1.68	1.78
2016	1.03	1.11	1.21	1.29	1.42	1.42	1.56	1.66	1.81	1.95
2017	1.00	1.08	1.20	1.28	1.43	1.43	1.61	1.72	1.89	2.04
2018	0.98	1.07	1.19	1.29	1.45	1.46	1.65	1.77	1.97	2.15

At the 'Lower' and 'Upper' bounds x% of the simulated prices were less. The confidence bounds are the regions between the 'Upper' and 'Lower' bounds.

Pollock fillet return volatility projections

Hist. Avg.	2015	2016	2017	2018	Long-run
14.84	14.84	14.84	14.84	14.84	14.84

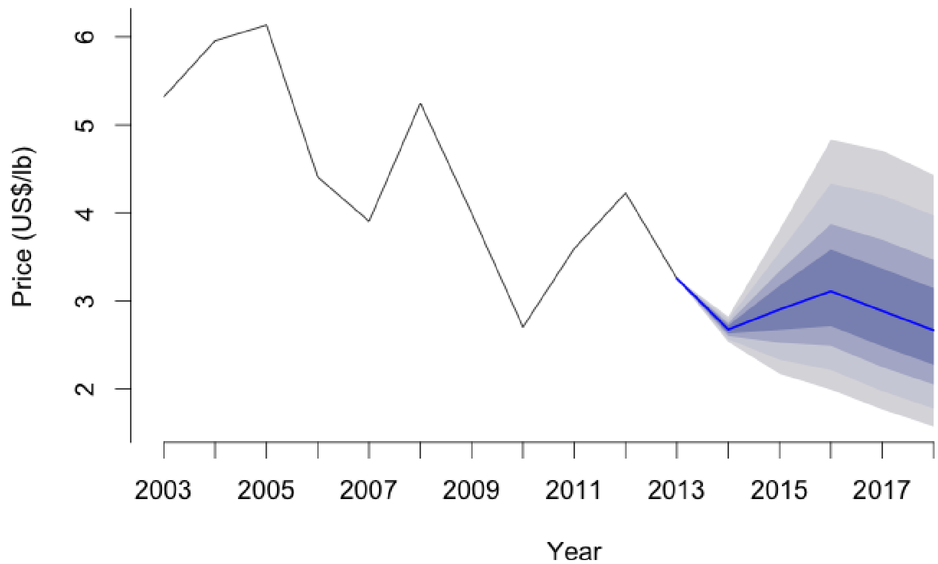

Figure 4.– Pollock roe price projections and confidence bounds.

Table 8.– Projected mean, probability bounds of first-wholesale pollock roe prices.

	Lower						Upper			
	5%	10%	20%	30%	Mean	Median	70%	80%	90%	95%
2014	2.53	2.56	2.60	2.63	2.67	2.67	2.72	2.75	2.79	2.82
2015	2.17	2.33	2.53	2.67	2.90	2.92	3.17	3.34	3.55	3.81
2016	1.99	2.21	2.49	2.71	3.11	3.11	3.58	3.87	4.33	4.83
2017	1.77	1.97	2.25	2.48	2.89	2.89	3.37	3.69	4.20	4.71
2018	1.57	1.78	2.05	2.27	2.67	2.68	3.15	3.47	3.97	4.43

At the 'Lower' and 'Upper' bounds x% of the simulated prices were less. The confidence bounds are the regions between the 'Upper' and 'Lower' bounds.

Pollock roe return volatility projections

Hist. Avg.	2015	2016	2017	2018	Long-run
20.10	17.69	20.32	19.91	20.28	20.22

The now-cast price projections for the year 2014 displays a modest degree of variation with the 90% confidence bounds within approximately 1.5% of the projected price. The accuracy of the now-cast predictions is a reflection of the fact that the majority of these products are exported, thus export prices are a strong predictor of first-wholesale prices.

As prices are projected past 2014 the confidence bounds grow reflecting increased uncertainty further out in the future. Price projections for the years 2015 to 2018 typically display some degree of mean reversion as prices attempt to stabilize the equilibrium trends estimated by the ARMA and ETS models. The mean price projection for surimi is fairly stable however there is considerable uncertainty as displayed by the wide confidence bounds (Fig. 2). While the estimated volatility for surimi is substantial it is expected to remain constant over 2015 to 2018 (Tables 6). Fillet price projection shows a slight upward trend in the mean (Fig. 3) and are slightly less volatile relative to surimi (Table 7). The mean price projection for roe is more erratic which is likely a reflection that the precipitous decline since 2005 has left the current price far from the estimated steady state (Fig. 4). Furthermore, the recent volatility is expected to persist as predicted to increase roe volatility is predicted to increase over 2015 to 2018 (Fig. 8).

Conclusions

This report describes the methodology applied in projecting annual prices of Alaska fisheries first-wholesale products in the Stock Assessment and Fishery Evaluation Report for the Groundfish Fisheries of the Gulf of Alaska and Bering Sea/Aleutian Island Area: Economic Status of the Groundfish Fisheries Off Alaska, 2013 Fissel et al. (2014). The data and methods described are intended to be sufficient for the reader to evaluate and reproduce the methods.

An empirical illustration of the forecast methods has been included to show how the described methods were applied. Now-casts for the year 2014 were made with fairly high precision because of the availability of contemporaneous data related to the product markets for which predictions are being made. Price projections for the years 2015 to 2018 contain considerably more uncertainty, however; the predictive densities retrospectively are consistent in the sense that they accurately reflect historically deviation from the models. Quantiles of the predictive distribution are shown to give a probabilistic characterization of the range of future prices. Thus, the methods and resultant price projections give policymakers, researchers, and the public accurate, contemporaneous first-wholesale price information and realistic bounds for the range of future prices.

The Economics and Social Sciences Research Program at the Alaska Fisheries Science Center plans to continue to include price projections as a component of the annual Economic SAFE. As forecasting methods are improved in the future or new data elements are incorporated, these methods may be revised. Any new methods will be published in future technical documents.

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Coefficient Tables

Table 9.– ARMA model AICc and coefficients.

product	model	AICc	intercept	ar1	ar2	ar3	ma1	ma2	ma3
PLCK Suri	ARMA(0,3)	210.62	-1.45				-0.79	0.91	0.10
PLCK Suri	ARMA(1,0)	210.24	-0.67	-0.54					
PLCK Suri	ARMA(2,0)	213.10	-0.50	-0.58	-0.08				
PLCK Suri	ARMA(3,0)	214.66	-1.08	-0.60	0.10	0.33			
PLCK Suri	ARMA(0,0)	213.21	-1.70						
PLCK Suri	ARMA(1,1)	213.15	-0.58	-0.49			-0.07		
PLCK Suri	ARMA(2,1)	216.49	-0.78	-0.06	0.28		-0.47		
PLCK Suri	ARMA(0,2)	207.45	-1.24				-0.86	1.00	
PLCK Suri	ARMA(0,1)	211.53	-0.36				-0.43		
PLCK Suri	ARMA(1,2)	210.63	-1.45	0.10			-0.89	1.00	
PLCK Roe	ARMA(0,2)	205.98	-2.36				-0.26	-0.74	
PLCK Roe	ARMA(1,2)	209.00	-2.40	0.14			-0.30	-0.69	
PLCK Roe	ARMA(0,3)	208.34	-2.47				0.05	-0.70	-0.35
PLCK Roe	ARMA(2,1)	205.05	-2.37	0.14	-0.68		-0.18		
PLCK Roe	ARMA(2,0)	202.06	-2.32	0.05	-0.68				
PLCK Roe	ARMA(3,0)	205.08	-2.36	-0.03	-0.68	-0.11			
PLCK Roe	ARMA(0,0)	210.97	-3.02						
PLCK Roe	ARMA(1,0)	213.60	-3.06	0.04					
PLCK Roe	ARMA(0,1)	211.82	-3.18				0.53		
PLCK Roe	ARMA(1,1)	213.36	-2.97	-0.35			0.72		
PLCK Flt	ARMA(1,0)	192.07	0.67	-0.07					
PLCK Flt	ARMA(2,0)	190.49	1.22	-0.11	-0.45				
PLCK Flt	ARMA(1,1)	192.51	1.74	0.64			-1.00		
PLCK Flt	ARMA(2,1)	192.58	1.18	-0.36	-0.50		0.32		
PLCK Flt	ARMA(3,0)	191.37	0.89	0.03	-0.41	0.33			

PLCK Flt	ARMA(0,1)	191.77	0.92				-0.23		
PLCK Flt	ARMA(0,0)	189.52	0.57						
PLCK Flt	ARMA(0,3)	194.15	0.61				0.02	-0.27	0.40
PLCK Flt	ARMA(0,2)	190.83	2.15				-0.23	-0.77	
PLCK Flt	ARMA(1,2)	193.77	2.00	0.23			-0.37	-0.63	
PLCK DsFlt	ARMA(1,0)	159.21	1.91	-0.12					
PLCK DsFlt	ARMA(0,3)	164.32	2.08				-0.42	-0.20	-0.39
PLCK DsFlt	ARMA(1,1)	162.23	1.91	-0.42			0.30		
PLCK DsFlt	ARMA(2,1)	165.70	1.91	-0.21	0.05		0.11		
PLCK DsFlt	ARMA(0,2)	162.20	1.91				-0.09	0.10	
PLCK DsFlt	ARMA(0,0)	156.75	1.92						
PLCK DsFlt	ARMA(0,1)	159.24	1.91				-0.10		
PLCK DsFlt	ARMA(2,0)	162.20	1.91	-0.11	0.07				
PLCK DsFlt	ARMA(1,2)	165.67	1.91	-0.20			0.10	0.08	
PLCK DsFlt	ARMA(3,0)	165.66	1.91	-0.11	0.06	-0.04			
PLCK Other	ARMA(2,1)	196.44	5.43	-0.03	0.05		-1.00		
PLCK Other	ARMA(1,1)	193.18	5.44	-0.03			-1.00		
PLCK Other	ARMA(0,3)	196.40	5.42				-1.03	0.12	-0.09
PLCK Other	ARMA(0,2)	193.19	5.44				-1.03	0.03	
PLCK Other	ARMA(0,1)	190.25	5.43				-1.00		
PLCK Other	ARMA(0,0)	200.51	4.47						
PLCK Other	ARMA(1,0)	196.26	4.80	-0.52					
PLCK Other	ARMA(2,0)	196.81	4.99	-0.70	-0.32				
PLCK Other	ARMA(1,2)	196.49	5.44	-0.38			-0.65	-0.35	
PLCK Other	ARMA(3,0)	200.09	5.01	-0.72	-0.35	-0.04			
PCOD Flt	ARMA(1,0)	191.07	1.82	-0.11					
PCOD Flt	ARMA(2,0)	192.43	2.05	-0.14	-0.26				
PCOD Flt	ARMA(3,0)	195.64	2.09	-0.16	-0.27	-0.06			
PCOD Flt	ARMA(0,0)	188.66	1.76						

PCOD Flt	ARMA(1,1)	190.24	2.79	0.53			-1.00		
PCOD Flt	ARMA(2,1)	192.98	2.92	0.59	-0.16		-1.00		
PCOD Flt	ARMA(0,2)	189.87	2.98				-0.46	-0.54	
PCOD Flt	ARMA(0,1)	190.78	1.94				-0.23		
PCOD Flt	ARMA(0,3)	192.93	2.93				-0.41	-0.48	-0.10
PCOD Flt	ARMA(1,2)	192.86	2.90	0.24			-0.64	-0.36	
PCOD H&G	ARMA(1,1)	200.09	2.26	0.72			-1.00		
PCOD H&G	ARMA(2,1)	203.12	2.53	0.78	-0.12		-1.00		
PCOD H&G	ARMA(0,1)	198.79	1.21				-0.07		
PCOD H&G	ARMA(0,0)	196.22	1.17						
PCOD H&G	ARMA(1,0)	198.82	1.19	-0.05					
PCOD H&G	ARMA(2,0)	201.35	1.40	-0.06	-0.14				
PCOD H&G	ARMA(3,0)	203.64	1.84	-0.10	-0.17	-0.22			
PCOD H&G	ARMA(1,2)	203.15	2.47	0.62			-0.85	-0.15	
PCOD H&G	ARMA(0,3)	202.61	2.89				-0.23	-0.30	-0.47
PCOD H&G	ARMA(0,2)	201.11	1.67				-0.13	-0.18	
PCOD Other	ARMA(0,3)	196.72	0.09				0.13	-0.53	0.01
PCOD Other	ARMA(0,2)	193.41	0.11				0.14	-0.54	
PCOD Other	ARMA(1,2)	196.72	0.10	-0.01			0.15	-0.53	
PCOD Other	ARMA(0,0)	194.00	-0.81						
PCOD Other	ARMA(1,0)	196.59	-0.89	0.06					
PCOD Other	ARMA(2,0)	193.96	0.02	0.06	-0.48				
PCOD Other	ARMA(3,0)	197.27	0.02	0.06	-0.48	0.00			
PCOD Other	ARMA(0,1)	196.08	-1.06				0.37		
PCOD Other	ARMA(1,1)	196.61	-0.86	-0.49			0.85		
PCOD Other	ARMA(2,1)	197.04	-0.20	-0.36	-0.43		0.54		
SABL H&G	ARMA(0,0)	184.96	3.47						
SABL H&G	ARMA(1,0)	187.61	3.48	-0.03					
SABL H&G	ARMA(2,0)	188.73	3.63	-0.03	-0.29				

SABL H&G	ARMA(3,0)	191.89	3.73	-0.06	-0.31	-0.10			
SABL H&G	ARMA(0,1)	187.59	3.49				-0.06		
SABL H&G	ARMA(1,1)	186.56	3.77	0.54			-1.00		
SABL H&G	ARMA(2,1)	187.98	3.83	0.65	-0.29		-1.00		
SABL H&G	ARMA(0,2)	184.42	3.82				-0.32	-0.68	
SABL H&G	ARMA(1,2)	187.67	3.81	0.09			-0.38	-0.62	
SABL H&G	ARMA(0,3)	187.69	3.82				-0.30	-0.66	-0.05
YLWS H&G	ARMA(3,0)	190.91	1.49	-0.07	-0.11	-0.11			
YLWS H&G	ARMA(0,1)	185.13	1.28				-0.07		
YLWS H&G	ARMA(1,1)	186.17	2.06	0.72			-1.00		
YLWS H&G	ARMA(2,1)	189.28	2.20	0.78	-0.10		-1.00		
YLWS H&G	ARMA(0,2)	187.82	1.42				-0.08	-0.11	
YLWS H&G	ARMA(1,2)	189.30	2.18	0.65			-0.88	-0.12	
YLWS H&G	ARMA(0,3)	190.88	1.69				-0.10	-0.14	-0.13
YLWS H&G	ARMA(1,0)	185.14	1.27	-0.05					
YLWS H&G	ARMA(2,0)	187.89	1.37	-0.06	-0.10				
YLWS H&G	ARMA(0,0)	182.54	1.27						
RCKS H&GwR	ARMA(2,0)	203.99	-2.61	-0.17	-0.25				
RCKS H&GwR	ARMA(0,3)	201.25	-2.40				-0.45	-0.23	-0.32
RCKS H&GwR	ARMA(1,1)	199.06	-2.32	0.37			-1.00		
RCKS H&GwR	ARMA(2,1)	201.14	-2.30	0.43	-0.24		-1.00		
RCKS H&GwR	ARMA(3,0)	201.27	-2.74	-0.27	-0.24	-0.58			
RCKS H&GwR	ARMA(0,1)	199.16	-2.22				-1.00		
RCKS H&GwR	ARMA(0,0)	199.90	-2.91						
RCKS H&GwR	ARMA(1,0)	202.00	-2.75	-0.16					
RCKS H&GwR	ARMA(0,2)	198.66	-2.30				-0.62	-0.38	
RCKS H&GwR	ARMA(1,2)	201.85	-2.32	0.15			-0.73	-0.27	
RCKS H&G	ARMA(1,2)	212.10	0.66	-0.84			0.22	-0.37	
RCKS H&G	ARMA(0,3)	210.01	1.37				-0.78	0.14	-0.36

RCKS H&G	ARMA(0,0)	210.49	-0.16						
RCKS H&G	ARMA(1,0)	206.56	0.21	-0.51					
RCKS H&G	ARMA(0,2)	209.01	1.63				-0.84	-0.16	
RCKS H&G	ARMA(3,0)	212.01	0.48	-0.53	-0.14	-0.20			
RCKS H&G	ARMA(0,1)	206.41	0.84				-0.61		
RCKS H&G	ARMA(1,1)	209.36	0.70	-0.09			-0.52		
RCKS H&G	ARMA(2,0)	209.51	0.24	-0.52	-0.02				
RCKS H&G	ARMA(2,1)	210.42	1.25	0.23	0.26		-1.00		
GLDT H&G	ARMA(1,0)	216.88	2.90	-0.28					
GLDT H&G	ARMA(2,0)	216.36	3.19	-0.38	-0.38				
GLDT H&G	ARMA(3,0)	219.27	3.20	-0.44	-0.43	-0.14			
GLDT H&G	ARMA(0,0)	216.05	3.06						
GLDT H&G	ARMA(1,1)	212.79	2.74	0.22			-1.00		
GLDT H&G	ARMA(2,1)	215.50	2.74	0.24	-0.16		-1.00		
GLDT H&G	ARMA(0,2)	212.34	2.76				-0.69	-0.31	
GLDT H&G	ARMA(0,1)	210.91	2.71				-1.00		
GLDT H&G	ARMA(0,3)	215.17	2.77				-0.72	-0.46	0.18
GLDT H&G	ARMA(1,2)	213.76	2.81	-0.59			0.00	-1.00	
ARTH H&G	ARMA(1,1)	221.90	5.02	-0.13			-1.00		
ARTH H&G	ARMA(2,1)	224.55	5.13	-0.18	-0.19		-1.00		
ARTH H&G	ARMA(0,1)	219.32	5.01				-1.00		
ARTH H&G	ARMA(0,0)	231.66	4.80						
ARTH H&G	ARMA(1,0)	228.04	3.94	-0.51					
ARTH H&G	ARMA(2,0)	225.05	5.27	-0.73	-0.59				
ARTH H&G	ARMA(3,0)	226.83	5.31	-0.88	-0.74	-0.34			
ARTH H&G	ARMA(1,2)	224.84	5.07	0.35			-1.55	0.55	
ARTH H&G	ARMA(0,3)	224.68	5.10				-1.17	0.04	0.14
ARTH H&G	ARMA(0,2)	221.73	5.04				-1.19	0.19	
FLTS H&G	ARMA(2,0)	190.22	3.01	0.27	-0.14				

FLTS H&G	ARMA(0,3)	189.21	2.83				-0.13	-0.41	-0.46
FLTS H&G	ARMA(1,1)	190.51	3.12	0.11			0.14		
FLTS H&G	ARMA(2,1)	187.87	2.67	0.98	-0.46		-1.00		
FLTS H&G	ARMA(3,0)	190.52	2.76	0.23	-0.01	-0.37			
FLTS H&G	ARMA(0,1)	187.59	3.13				0.23		
FLTS H&G	ARMA(0,0)	186.17	3.35						
FLTS H&G	ARMA(1,0)	187.64	3.17	0.23					
FLTS H&G	ARMA(0,2)	190.28	3.09				0.31	0.16	
FLTS H&G	ARMA(1,2)	191.91	2.96	-0.95			1.35	0.47	
REXS Whole	ARMA(0,1)	178.68	1.77				0.19		
REXS Whole	ARMA(1,1)	180.84	1.79	-0.72			1.00		
REXS Whole	ARMA(0,3)	179.62	0.20				-0.21	-0.48	-0.32
REXS Whole	ARMA(2,1)	179.09	-0.08	0.71	-0.44		-1.00		
REXS Whole	ARMA(3,0)	181.25	0.87	-0.02	-0.36	-0.27			
REXS Whole	ARMA(0,2)	177.07	0.08				-0.33	-0.67	
REXS Whole	ARMA(0,0)	176.34	1.60						
REXS Whole	ARMA(1,0)	178.90	1.70	0.09					
REXS Whole	ARMA(2,0)	179.32	1.13	0.09	-0.37				
REXS Whole	ARMA(1,2)	180.05	0.19	0.25			-0.50	-0.50	
SHAL Flt	ARMA(1,2)	199.18	-1.05	0.49			-0.99	-0.01	
SHAL Flt	ARMA(1,0)	195.80	-1.63	-0.24					
SHAL Flt	ARMA(2,0)	197.16	-1.51	-0.32	-0.28				
SHAL Flt	ARMA(3,0)	200.46	-1.51	-0.33	-0.28	-0.02			
SHAL Flt	ARMA(0,3)	199.20	-0.33				-0.52	0.26	0.64
SHAL Flt	ARMA(0,0)	194.52	-1.65						
SHAL Flt	ARMA(1,1)	195.87	-1.05	0.49			-1.00		
SHAL Flt	ARMA(0,2)	196.49	-0.94				-0.57	-0.43	
SHAL Flt	ARMA(0,1)	195.02	-1.57				-0.36		
SHAL Flt	ARMA(2,1)	200.46	-1.51	-0.30	-0.27		-0.02		

AMAK H&G	ARMA(0,2)	215.66	3.22				-0.16	-0.15	
AMAK H&G	ARMA(0,3)	217.59	3.59				0.11	-0.19	-0.40
AMAK H&G	ARMA(2,0)	215.48	3.32	-0.10	-0.24				
AMAK H&G	ARMA(1,2)	218.91	3.23	0.14			-0.28	-0.13	
AMAK H&G	ARMA(0,0)	211.13	2.90						
AMAK H&G	ARMA(1,0)	213.64	2.89	-0.08					
AMAK H&G	ARMA(2,1)	218.30	3.40	0.16	-0.25		-0.29		
AMAK H&G	ARMA(3,0)	216.64	3.46	-0.17	-0.25	-0.32			
AMAK H&G	ARMA(0,1)	213.52	2.92				-0.15		
AMAK H&G	ARMA(1,1)	215.98	3.11	0.40			-0.58		
RCKF H&G	ARMA(1,0)	202.70	0.35	0.12					
RCKF H&G	ARMA(1,1)	203.30	0.72	-0.65			1.00		
RCKF H&G	ARMA(2,0)	203.48	0.96	0.16	-0.32				
RCKF H&G	ARMA(3,0)	205.17	1.20	0.08	-0.28	-0.28			
RCKF H&G	ARMA(0,1)	202.42	0.40				0.21		
RCKF H&G	ARMA(0,3)	206.35	1.38				0.05	-0.38	-0.11
RCKF H&G	ARMA(2,1)	205.69	1.24	0.53	-0.39		-0.44		
RCKF H&G	ARMA(0,2)	202.88	1.78				0.25	-0.75	
RCKF H&G	ARMA(1,2)	205.44	1.75	0.52			-0.56	-0.44	
RCKF H&G	ARMA(0,0)	200.34	0.41						

Table 10.– ETS model AICc and coefficients.

product	model	AICc	alpha	beta	l	b
PLCK Suri	ETS(AAN)	226.42	0.05	0.05	-16.40	3.85
PLCK Suri	ETS(ANN)	218.81	0.00		-1.69	
PLCK Roe	ETS(ANN)	216.57	0.00		-3.06	
PLCK Roe	ETS(AAN)	221.87	0.00	0.00	3.16	-0.55
PLCK Flt	ETS(ANN)	195.12	0.00		0.57	
PLCK Flt	ETS(AAN)	203.49	0.00	0.00	-7.48	1.87
PLCK DsFlt	ETS(AAN)	166.03	0.00	0.00	3.94	-0.16
PLCK DsFlt	ETS(ANN)	159.95	0.00		1.92	
PLCK Other	ETS(AAN)	211.81	0.00	0.00	2.01	0.25
PLCK Other	ETS(ANN)	206.11	0.00		4.47	
PCOD Flt	ETS(AAN)	202.89	0.05	0.05	-3.83	1.82
PCOD Flt	ETS(ANN)	194.26	0.00		1.76	
PCOD H&G	ETS(ANN)	201.82	0.00		1.17	
PCOD H&G	ETS(AAN)	207.17	0.00	0.00	2.57	-0.23
PCOD Other	ETS(ANN)	199.61	0.00		-0.81	
PCOD Other	ETS(AAN)	205.47	0.02	0.00	0.63	-0.18
SABL H&G	ETS(ANN)	190.56	0.00		3.49	
SABL H&G	ETS(AAN)	196.08	0.00	0.00	8.31	-0.38
YLWS H&G	ETS(ANN)	188.15	0.00		1.26	
YLWS H&G	ETS(AAN)	197.00	0.03	0.03	0.72	1.38
RCKS H&GwR	ETS(AAN)	211.22	0.00	0.00	-2.60	-0.04
RCKS H&GwR	ETS(ANN)	205.51	0.00		-2.91	
RCKS H&G	ETS(AAN)	222.00	0.00	0.00	-7.39	0.51
RCKS H&G	ETS(ANN)	216.09	0.00		-0.17	
GLDT H&G	ETS(ANN)	221.65	0.00		3.06	
GLDT H&G	ETS(AAN)	227.74	0.00	0.00	10.82	-0.51
ARTH H&G	ETS(AAN)	242.87	0.00	0.00	15.38	-0.83

ARTH H&G	ETS(ANN)	237.26	0.00		4.79	
FLTS H&G	ETS(AAN)	197.55	0.00	0.00	4.06	0.03
FLTS H&G	ETS(ANN)	191.78	0.00		3.36	
REXS Whole	ETS(ANN)	180.71	0.00		1.61	
REXS Whole	ETS(AAN)	186.59	0.00	0.00	7.21	-0.40
SHAL Flt	ETS(AAN)	205.45	0.00	0.00	0.66	-0.25
SHAL Flt	ETS(ANN)	200.12	0.00		-1.66	
AMAK H&G	ETS(AAN)	220.42	0.00	0.00	-13.84	1.41
AMAK H&G	ETS(ANN)	216.73	0.00		2.89	
RCKF H&G	ETS(AAN)	211.52	0.00	0.00	-8.89	0.73
RCKF H&G	ETS(ANN)	205.95	0.00		0.41	

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